Characterising Changing Travel Patterns in the COVID-19 Era

Dr Fiona Crawford

Acknowledgements

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The number plate data used in this research was provided by the Bristol Traffic Control Service at Bristol City Council. The vehicle data was obtained through the DVLA's Vehicle Enquiry Service API[1].

Any views expressed in this report are those of the author.

Impacts

This research was presented at the TRANSITION Clean Air Network's Discovery & Innovation Summit in February 2022. As a direct result of this project, I have started to form connections with interested parties at the University of Birmingham, the Behavioural Insights meetings run by the Institute for Transport Studies in Leeds and other academic researchers. The research will be presented at the Universities' Transport Study Group conference in July 2022. Two academic journal papers are currently being drafted based on the research undertaken as well as a blog entry which will appear on a new blog launched by the Centre for Transport and Society.

This project has allowed me to greatly strengthen our team's connection with the traffic control and air quality teams at Bristol City Council. I presented my research to them in early 2022 and I am continuing to explore some aspects of the data that they are interested in.

Some anonymised data from this research, as well as code used to process the data, can be accessed here: https://github.com/ficrawford/TravelCovidBristolANPR and https://zenodo.org/record/6723265#.YrW-oHbMI2w.

[1] https://developer-portal.driver-vehicle-licensing.api.gov.uk/apis/vehicle-enquiry-service/vehicle-enquiry-service-description.html#vehicle-enquiry-service-api

Contents

Summary

The Covid-19 pandemic has resulted in an unprecedented 'shock' to regular traffic levels, in terms of the scale of the drop, the geographic coverage and the longevity of the impacts. Improvements in air quality were observed in many cities during the initial lockdown starting in March 2020, at least in terms of NOx, although emissions rose steadily through the summer of 2020 in most areas.

The aim of this project was to examine travel behaviour during the pandemic to inform policies related to air quality and decarbonisation. Travel behaviour at an aggregate level and individual travel behaviour were examined using Automatic Number Plate Recognition (ANPR) data from Bristol and the associated vehicle type and fuel type data.

Whilst at an aggregate level, traffic in Bristol had returned to pre-pandemic levels by mid-2021 (at the latest), this masked more complex changes in behaviour. By examining different paths taken within the Bristol network, this project identified two types of paths/routes based on how volumes have changed since early 2019. One group had traffic volumes just below pre-pandemic levels in mid-2021, whereas the other group saw a larger 'bounce-back' after restrictions were lifted.

Differences in the response to the pandemic were observed based on the frequency with which vehicles make trips in Bristol and the type of vehicle used. There are also many unobserved factors influencing behaviour. For example, frequent trip makers in Bristol who are observed in both the spring of 2019 and the spring of 2021 have had different responses with around half making similar numbers of trips in both periods and the remaining half fairly evenly split between vehicles making more trips in 2021 and vehicles making fewer trips.

Overall, the project has identified priorities for further work, including research to examine whether there are groups of former travellers who are still waiting to return to their previous trip making, policies to encourage more efficient and sustainable ways of transporting goods in urban areas, and an in-depth analysis of local origin-destination matrices to examine how routes have been affected differently by the pandemic.

1 Introduction

The aim of this project was to examine how travel behaviour in Bristol changed during different stages on the pandemic and the resulting impacts on air quality. The research uses Automatic Number Plate Recognition (ANPR) data obtained from the Traffic Control Service in Bristol as well as the DVLA Vehicle Enquiry Service API which provides vehicle information about submitted number plates, including vehicle type, fuel type, age and emissions. As well as providing information about travel in Bristol, the report also aims to present a methodology which can be used in other locations to examine changes in travel behaviour.

Section 2 of this report will provide some background to the Covid-19 pandemic in Bristol. Section 3 will describe the methodology used to process the data, to identify spatially similar trips, to identify geographical differences in the impact of the pandemic, and to segment the frequently observed vehicles into clusters with similar characteristics. Section 4 describes the data provided and presents the results of the analysis. Section 5 discusses the implications of the results for Bristol and at a national level before Section 6 concludes the report.

2 Travel and the Covid-19 pandemic in Bristol

The Covid-19 pandemic fundamentally changed activity patterns and travel behaviour from March 2020, particularly due to the effect of national and regional lockdowns and the closure of schools and businesses at various times in 2020 and early 2021. The Department for Transport reported that the number of vehicle miles on the road network in motorised vehicles was 21% lower in 2020 than it had been in 2019 (Department for Transport, 2021). Increases in working from home in some sectors as well as increases in online shopping also meant that the nature of the trips being undertaken was often different to pre-pandemic trips.

This report focuses on Bristol and, as shown in Figure 1, the overall pattern in terms of the relative change in presence at places of employment was similar to that observed on average in Great Britain. Although the pattern is very similar, a larger drop in time spent at workplaces was observed in Bristol during the first national lockdown and workplace presence has remained lower in Bristol relative to the baseline data (from January to February 2020) than the overall figures for Great Britain. This perhaps reflects the nature of employment in Bristol where a relatively high proportion of employees are able to work from home.

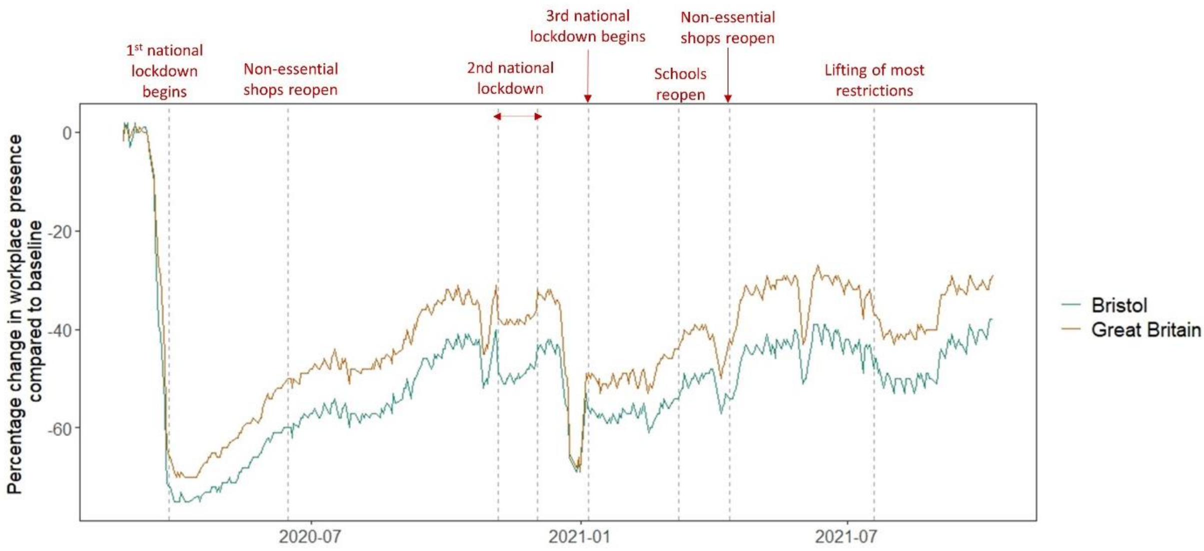

Figure 1: Data for Bristol and Great Britain from the Google Mobility Report for workplace presence along with a pandemic timeline (Source: Data from Google Covid-19 Community Mobility Reports[2])

Commuting behaviour did not just change due to home working as the pandemic also had an impact on unemployment. Figure 2 shows the proportion of residents in Bristol who were claiming unemployment benefits and a large increase is observed in April 2020.

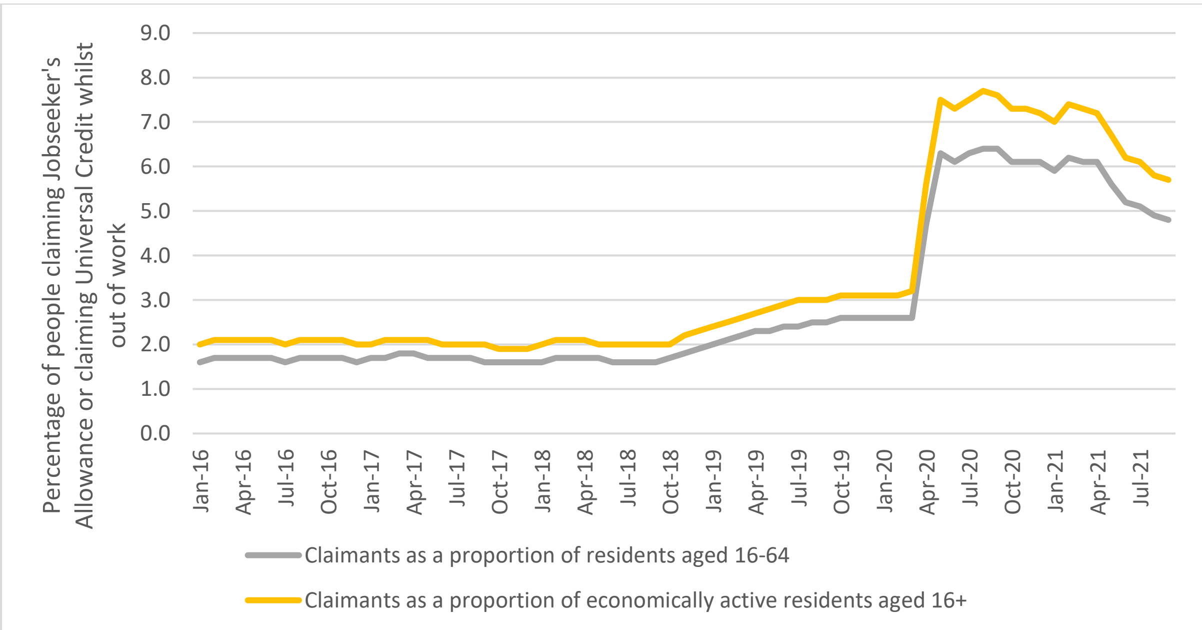

Figure 2: Proportion of residents in Bristol claiming Jobseeker's Allowance or claiming Universal Credit whilst out of work (Source: Data from Nomis[3])

[2] https://www.google.com/covid19/mobility/?hl=en
[3] https://www.nomisweb.co.uk/sources/cc

Data from the Automatic Urban and Rural Network (AURN) of air quality monitoring stations[4] can be used to examine trends over time. The data from AURN stations undergoes detailed verification and ratification and therefore only data from these stations in Bristol will be examined in this report. Data is available from two stations in Bristol: St Paul's, an urban background station, and Temple Way, an urban traffic station. Figure 3 shows how concentrations of key pollutants have changed between January 2018 and December 2021. This data has been deseasonalised using meteorological data from the site outside Bristol (using the R package worldmet) and the trend lines were estimated using Generalized Additive Modelling through the openair package in R (Carslaw & Ropkins, 2012). Note that the Temple Way station did not have data on O_3 or $PM_{2.5}$.

A step-change in NO_x was observed in early 2020, but NO_x levels have subsequently increased and it is not clear from a visual inspection whether levels in 2021 are significantly lower than they would have been without the impact of the pandemic on road travel.

This report will be examining the impact of the pandemic on travel behaviour. The air quality implications of any changes observed will be examined through the use of DVLA data associated with the vehicles observed. Whilst this will not allow a direct examination of changes in emissions, it will provide insights at a higher level into the types of vehicles using the Bristol road network and how this has changed between 2019 and 2021.

[4] https://uk-air.defra.gov.uk/networks/network-info?view=aurn

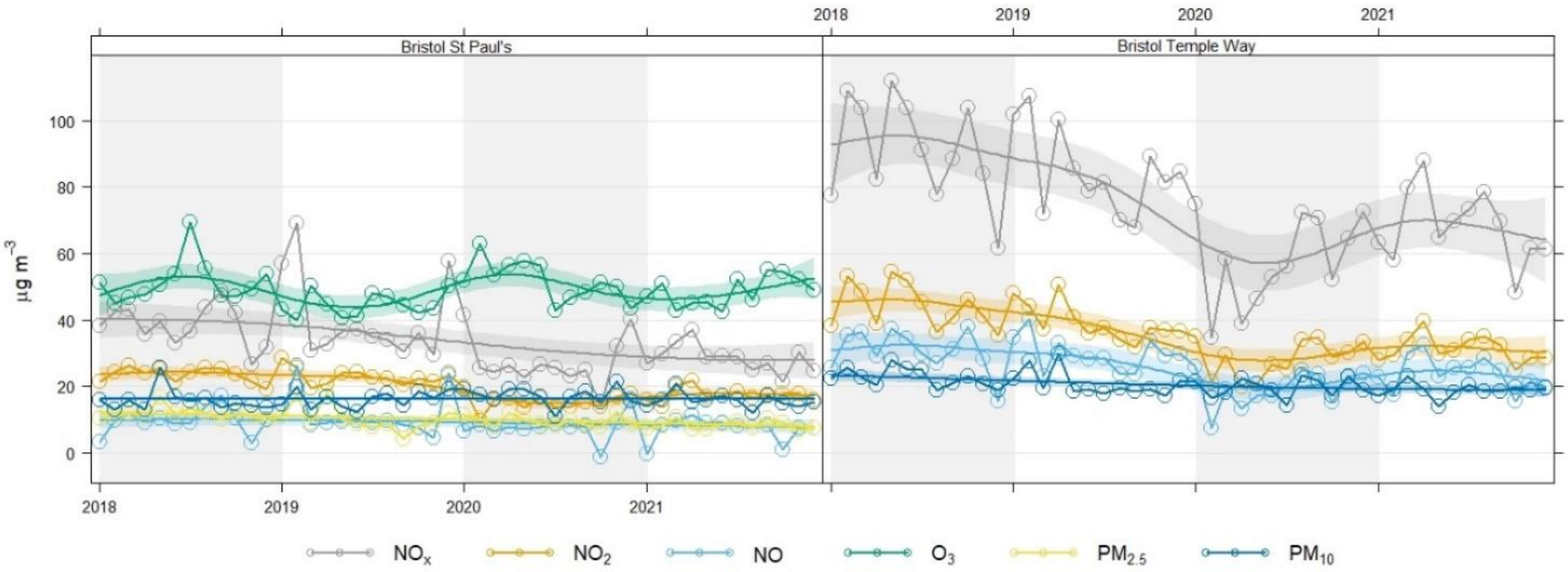

Figure 3: Air pollution measures from 2018 to 2021 from Bristol's AURN monitoring stations in St Paul's (Urban Background) and Temple Way (Urban Traffic)

3 Methodology

Data from 101 cameras within the Bristol City Council area was obtained for the period from 28/2/2019 to 30/09/2021. In total, 505,026,585 observations of number plates were recorded.

An in-depth analysis of available data was undertaken and then cameras with insufficient days of operation, days with ANPR system problems and number plates recorded with insufficient 'confidence' by the system were removed. Only number plates which were recognised by the system as being registered in Great Britain or Northern Ireland were retained. This was partly due to the lower confidence in the reading of non-UK plates by the system and it was partly because vehicle information (using the DVLA vehicle look-up system) was only available for UK plates. Non-UK licence plates accounted for only around 0.6% of the observations in the Bristol data. The removal of cameras from the analysis was not done entirely based on performance thresholds as the strategic importance of the location as well as the interaction with other cameras mounted at the same site also needed to be taken into account.

After cleaning, data for 64 cameras in 29 locations remained (Figure 4[5]). The data covered the period from 28/2/2019 to 30/9/2021 and 920 complete days of data were recorded. This cleaned data contained over 364 million observations.

[5] Please note that due to the multi-purpose nature of the cameras, more detailed location information cannot be provided.

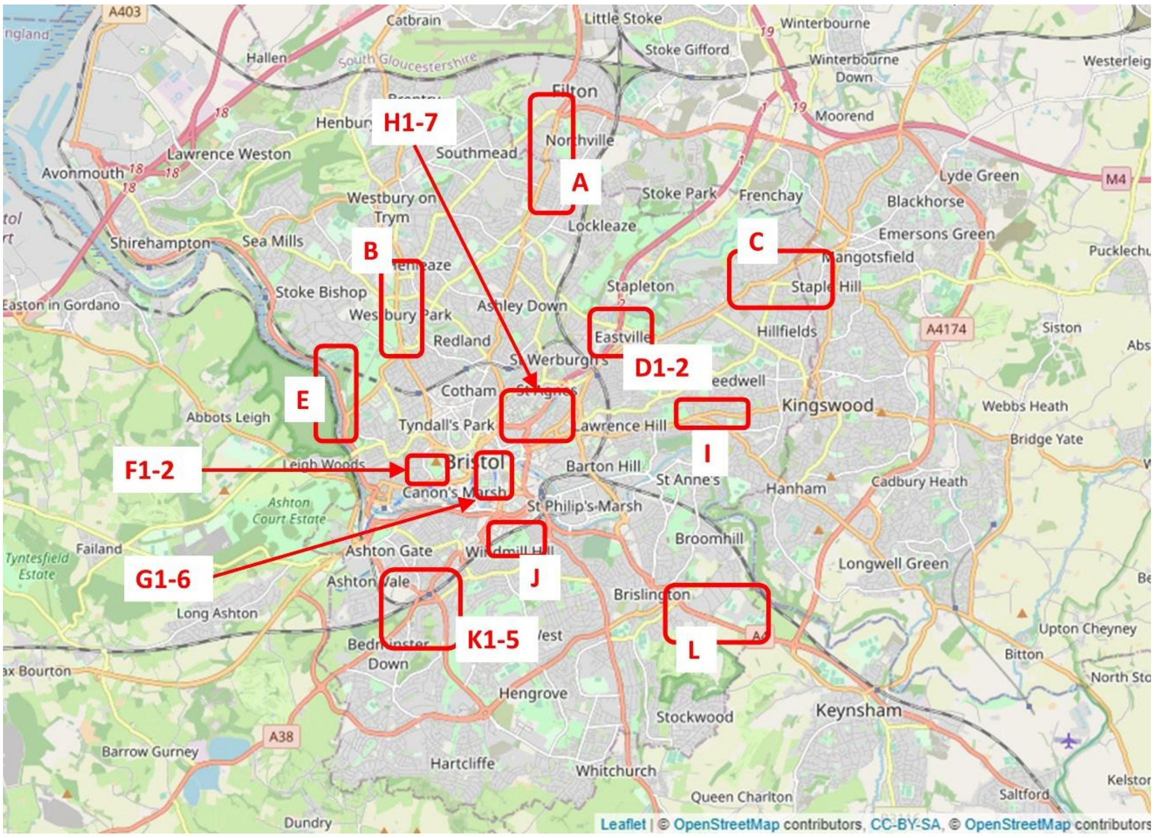

Figure 4: Locations of ANPR cameras used in the analysis

Each observation consists of a number plate, a date-time stamp and the camera at which it was recorded. To be useful, the observations needed to be linked up into trips. This is not straightforward as there is not a clear threshold to determine whether two observations by the same vehicle are part of the same trip or whether they are part of two separate trips (with an activity occurring between the two). A processing strategy was developed which used travel times between cameras from the Bing Maps API[6], travel times by surrounding vehicles recorded in the ANPR data, the distribution of travel times between each pair of cameras at each hour of the day, and a daily factor using system-wide travel times to identify anomalous days.

After processing the data into trips, almost 75 million trips remained which were made by 3,253,195 different vehicles.

Additional data about each of the vehicles observed was then obtained by making calls to the DVLA Vehicle Enquiry Service API[7]. The fields used in this research include the vehicle type, fuel type, Euro Standard and year of first registration. No personal data relating to the people registering or driving the vehicles was obtained. Not all number plates could be

[6] https://www.bingmapsportal.com/

[7] https://developer-portal.driver-vehicle-licensing.api.gov.uk/apis/vehicle-enquiry-service/vehicle-enquiry-service-description.html#introduction

identified in the DVLA database, perhaps due to errors in the recording of the number plates or because the vehicle was no longer registered in 2021.

3.1 Grouping spatially similar trips (spatial clustering)

Trips are made up of a string of observations at individual cameras, also known as a 'trip sequence'. Even if we simplify these by considering sites (which could have multiple cameras focused on different lanes of traffic or directions) rather than individual cameras, there is still a large number of permutations of the 29 sites, particularly since there is no limit on the number of sites in a single trip. In fact, 1.5 million different trip sequences were observed in the data. To reduce the dimensionality of this spatial aspect of the data, the following process was used to identify groups of 'spatially similar trips' so that the group identifier could be used as a proxy for the detailed sequence of observations making up each trip.

The methodology is described in more detail in Crawford et al. (2018) and the main steps are detailed in Figure 5.

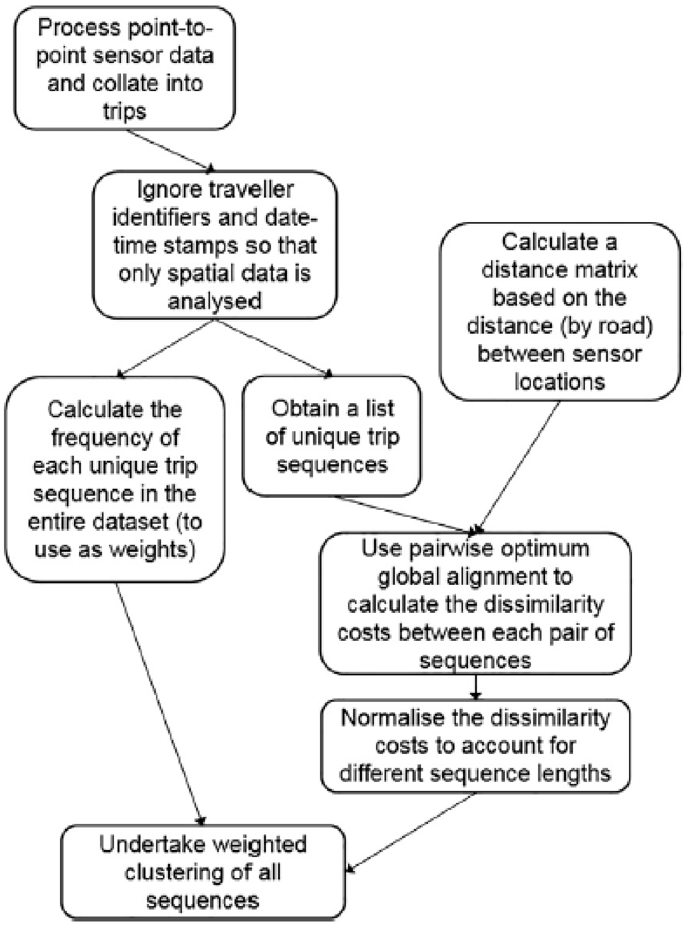

Figure 5: Process for identifying groups of spatially similar trips (Figure 2 from Crawford et al. (2018))

Computational limitations meant that undertaking this process on all of the different trip sequences observed was infeasible. The sequences were ranked according to the frequency with which they appeared in the data to decide which should be retained for the spatial clustering. To obtain 95% coverage of the trips observed, 12,505 trip sequences needed to be included in the spatial clustering process and this number was sufficiently small to allow the analysis to be undertaken without the need for High Performance Computing (HPC) facilities. This cut-off was equivalent to the selection of all sequences observed at least 113 times over the 31 month period by any vehicle.

After selecting the trip sequences for clustering (e.g. site A -> site C -> site F), each pair of sequences was compared using an optimal matching sequence alignment process to obtain the 'distance' between the two trip sequences. The matching process considers the distance between each of the sites in the trip sequences and also accounts for sites in one sequence which are not matched to a site in the second sequence.

This distance matrix was then used to undertake hierarchical clustering of the trip sequences, weighted by the number of observations of each sequence in the full dataset. To decide on the appropriate number of clusters to use, the following metrics were examined: Hubert's Gamma (Somers'D), Average Silhouette Width, Point Biserial Correlation and Hubert's C. The optimal number of clusters identified most frequently across these different metrics was 47, and therefore 47 spatial clusters were used for this research.

3.2 Dynamic time warping

For each of the groups of spatially similar trips identified using the method in Section 3.1, the time series of trip volumes for the period of data available was examined.

There are a wide variety of methods which can be used for clustering time series (see Aghabozorgi et al. (2015)). For the current analysis, Dynamic Time Warping was used for measuring the similarity between two time series as it does not assume that the timing of changes in the time series need to be the same, but it only considers the shape of the series. Figure 6 shows how this works in practice. For the current application, this means that we can compare time series based on the impact of the pandemic without assuming that all parts of the network will experience effects at exactly the same time.

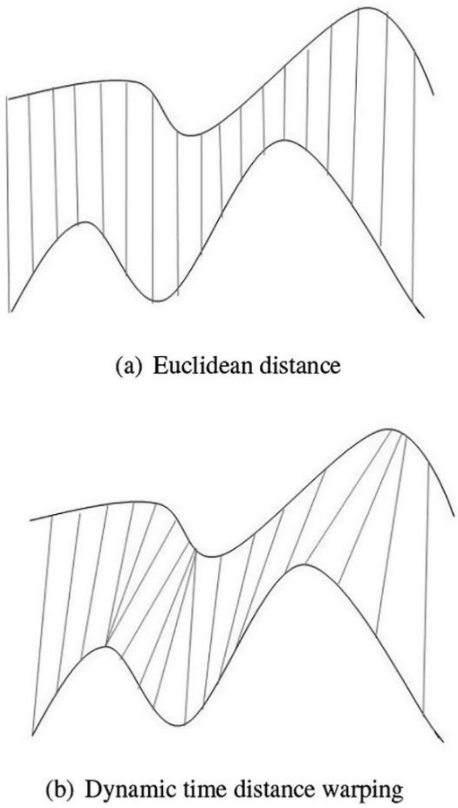

Figure 6: Example of matching using fixed time points versus dynamic time warping (Figure 1 in Li et al. (2021))

In the current application, one time series was obtained for each group of spatially similar trips. The time series consist of trips per month between March 2019 and September 2021. The 'distance' between each pair of time series can then be calculated using Dynamic Time Warping, before partitional clustering is undertaken to identify clusters of these time series. This research utilised the dtwclust package in R.

3.3 Traveller/vehicle clustering

Whilst it would be interesting to apply the time series clustering methodology to the trips made by individual vehicles, the number of vehicles involved makes the required computing power very large and therefore it is not feasible using the resources available for this research. An alternative method is therefore required which can segment vehicles based on their travel behaviour and examine change over time.

Examining changes over time is always challenging due to issues relating to seasonality, for example, but it is even harder during the pandemic due to the changing restrictions on behaviour and at times changes in behaviour in anticipation of changes. For this reason, this research will examine a subset of trips relating to the same months in 2019, 2020 and 2021 to compare the changes over time. The time period should be sufficiently large to allow an examination of different types of travel behaviour (for example monthly trips) but in 2020 and 2021, the national restrictions should be relatively constant over the time period. A period of 3 months was considered to be a good compromise. Data from April to June 2020 provides insight into the first national lockdown and the early stages of reopening in June, whereas by April to June 2021 schools had reopened and the stay-at-home order had been lifted.

As there is not much which can be determined from analysing vehicles which only appear a few times in the data, this analysis will be limited to frequently observed vehicles only. The same panel of vehicles will be examined in each of the three years and therefore many vehicles may have no trips recorded in any given year. Data from each year will be clustered independently using the following three clustering variables, calculated for each vehicle:

1. The number of trips made.
2. The number of spatial clusters used (as a measure of spatial coverage).
3. The standard deviation of all trip start times in the month (as a crude measure of temporal coverage).

Due to the large number of vehicles to cluster, a partitioning cluster method will be used. For each year, the optimal number of clusters will be identified using the elbow method.

4 Results

A summary of the data processing and analysis undertaken is shown in Figure 7. The results will be discussed for the raw number plate data first, then the processed ‘trip’ data, then details about the types of vehicles observed will be presented, followed by an examination of traveller behaviour.

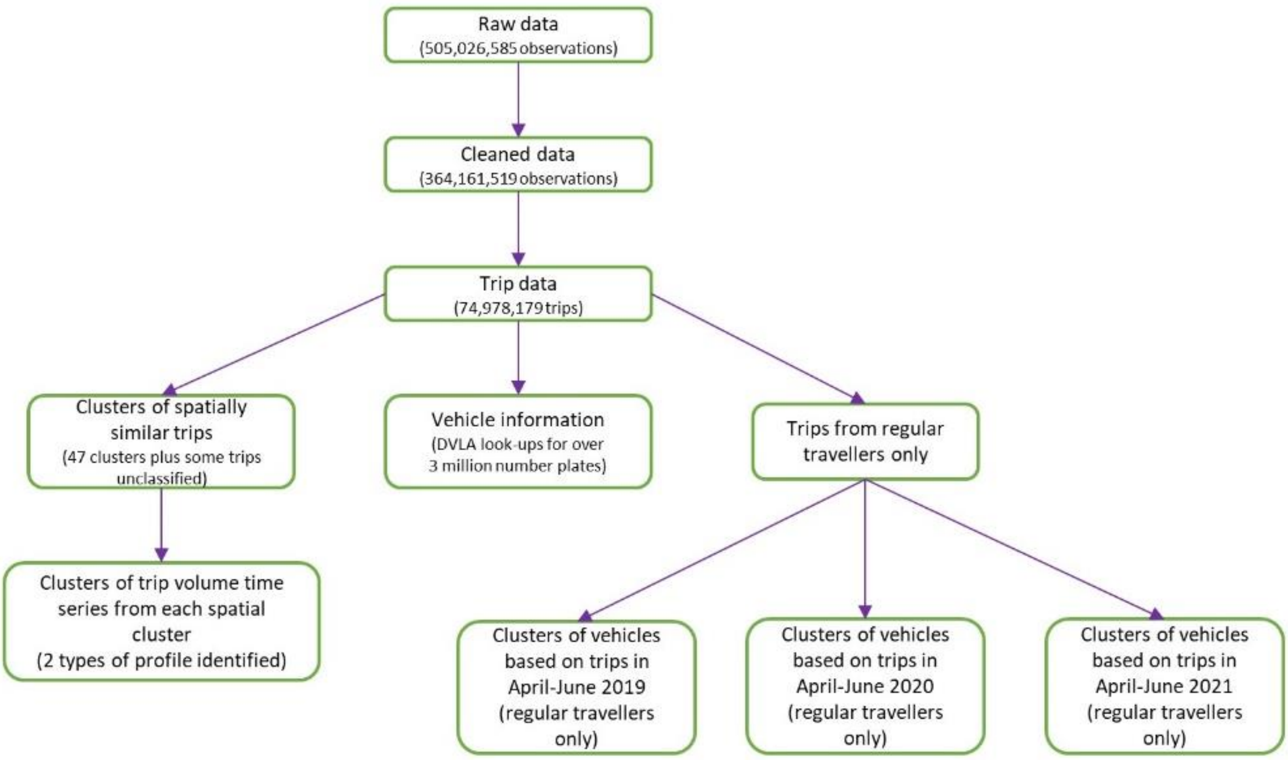

Figure 7: Overview of data processing and analysis undertaken

4.1 Number plates observed

As described in Section 3, a substantial amount of data cleaning was undertaken to obtain trip data for analysis. It is also useful, however, to explore the raw data as this gives an indication of the total number of vehicles observed before, for example, non-UK licence plates are removed during the cleaning process. The vehicle counts presented below only include data from the 64 cameras selected for the final analysis and the 920 days with sufficiently complete data. As the data has not been cleaned, there may be some cases of multiple reads of a number plate as it passes a camera one time or multiple reads of a number plate as it passes a set of cameras at one location, but the percentage of observations affected is assumed to be fairly constant over time.

Figure 8 shows the overall pattern in ANPR observations over the two and a half year period examined. As expected, the first year of data (up to March 2020) shows relatively consistent counts with typical seasonal patterns such as slightly lower counts during August and over Christmas. From March 2020, the counts follow a similar pattern to the workplace presence estimates from Google reported in Figure 1.

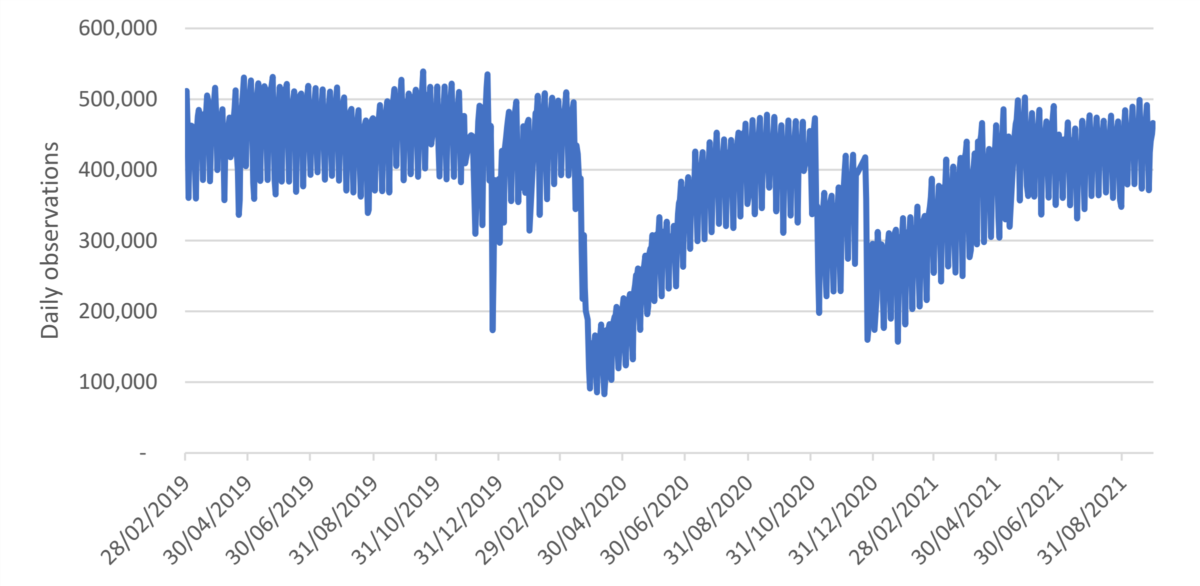

Figure 8: Total number of observations at the 64 cameras

Figure 9 shows the average number of observations per number plate per day. This was created in order to examine whether the trips during lockdowns were as a result of a few vehicles making many more trips, for example. Whilst there were decreases in the number of trips per number plate per day during the national lockdowns, the drop was small and the data for mid-2021 is similar to pre-pandemic data. This could be due to the time period considered as the number of trips per day can be constrained by the need for a return trip once the required location has been visited, for example.

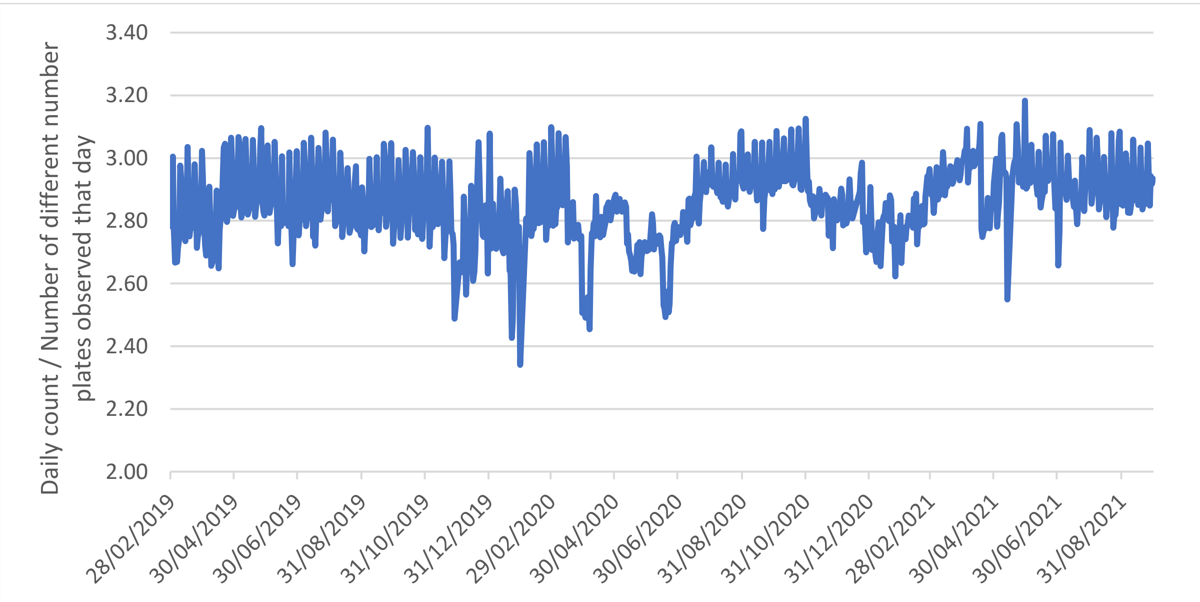

Figure 9: Average number of observations per number plate per day

Although non-UK registered number plates have been removed for the main analysis, they are present in the raw data. Figure 10 indicates the percentage of observations which were recorded as UK plates for each day. An increase in the proportion of non-UK plates is observed in the summer of 2019, perhaps as a result of tourism, but a much smaller and more gradual seasonal effect is observed in 2020 and 2021. As the type of vehicles could not be determined for non-UK plates in this research, it was not possible to differentiate between the trend for non-UK registered cars and non-UK Heavy Goods Vehicles (HGVs). As well as the Covid-19 pandemic, there is also likely to be an impact of the UK leaving the European Union in January 2020.

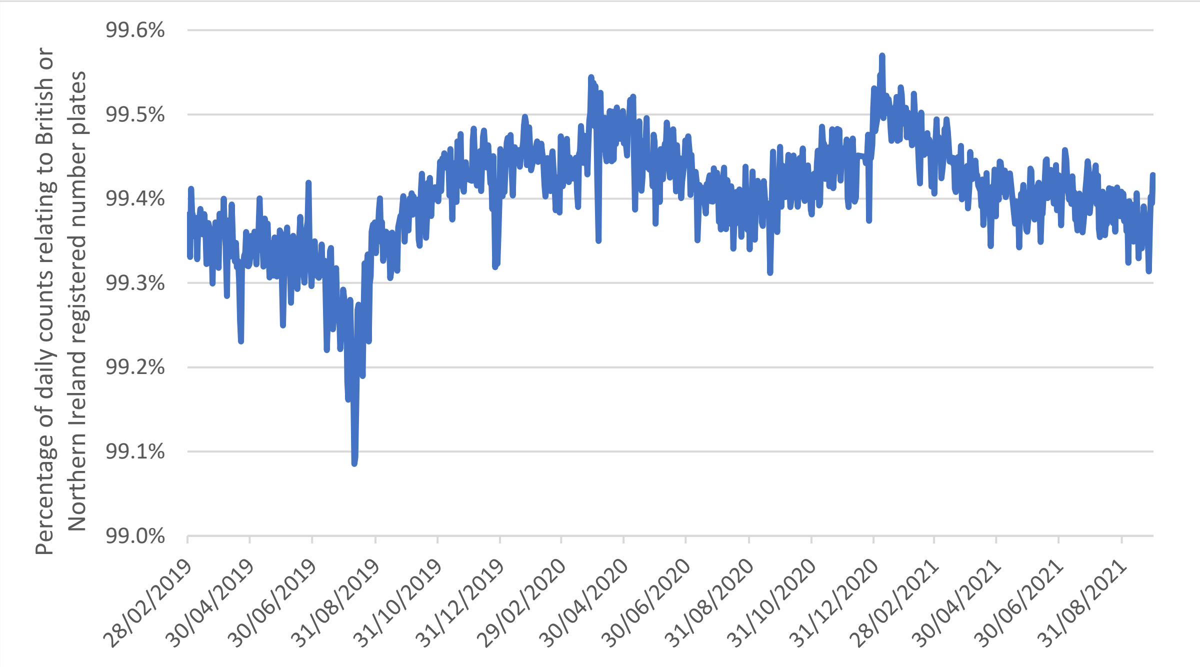

Figure 10: Percentage of observations categorised as UK plates (prior to cleaning)

4.2 Trip data

After cleaning the data and processing the observations into trips, almost 75 million trips remained for the analysis. Figure 11 shows the number of trips per month in the data and the overall pattern is consistent with the volumes observed in the raw observation data. Figure 12 shows a similar pattern in the number of vehicles observed per month. This suggests that the drop in trips during lockdowns was not due to most people halving the number of trips they make per month, for example, it was due to a substantial proportion of people no longer making any trips in their vehicle in the Bristol area.

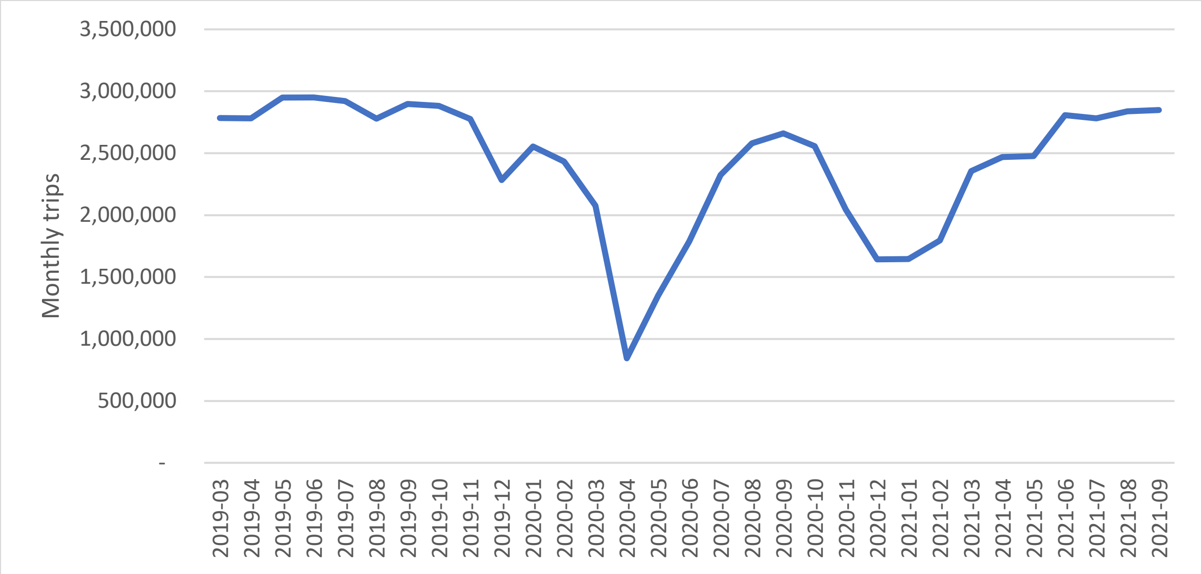

Figure 11: Trips per month in the cleaned data

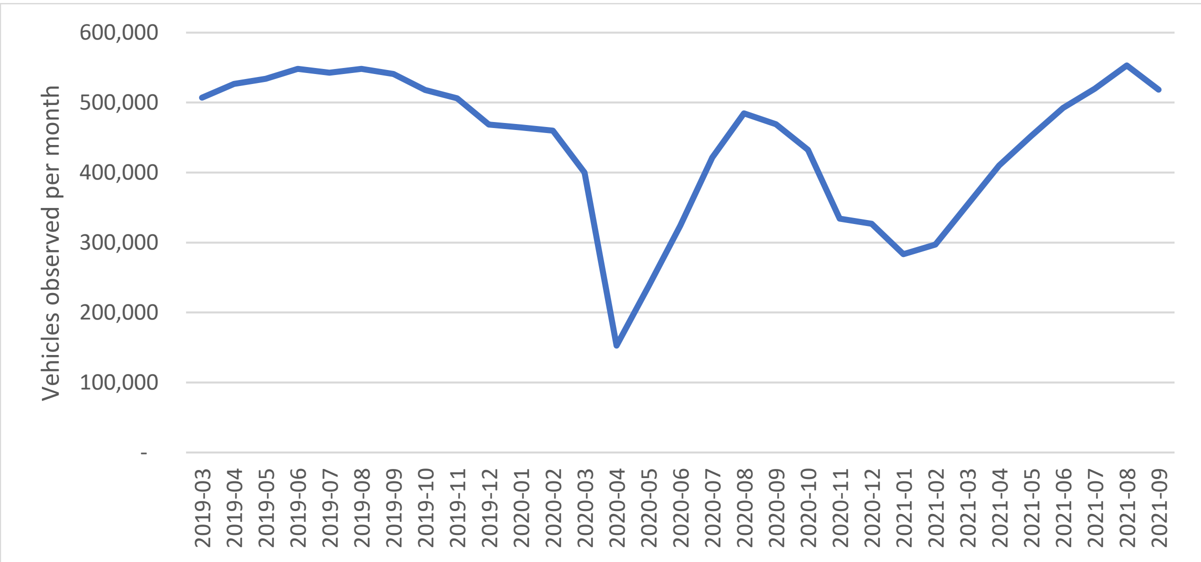

Figure 12: Number of vehicles observed per month in the cleaned data

An analysis of the split of trips across days of the week suggested that there was no systematic change over the time period analysed. The split of trips according to the time of day was also examined and Figure 13 shows the monthly percentage of trips during the morning and evening peak periods. These percentages are relatively consistent over time. Although there has been much discussion about less 'peaked' daily traffic flow profiles due to more homeworking, the data shows that during lockdowns there was a slightly higher proportion of trips during the peak periods. This is likely to be because off-peak trips for purposes such as shopping and entertainment were affected even more than commuting trips.

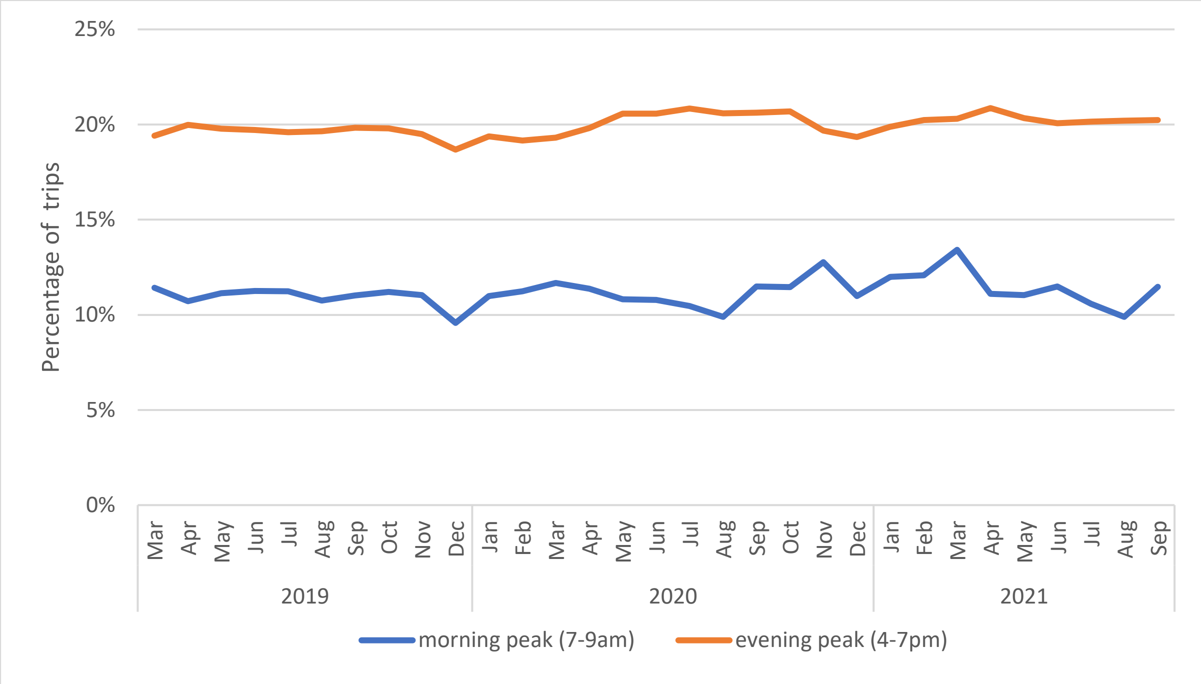

Figure 13: Monthly percentage of trips during the morning and evening peak

As well as examining the number of trips, it is also possible to examine whether trips are made by frequently observed vehicles or more occasional visitors. Figure 14 shows the number of trips observed in each month and the colours represent the nature of the vehicles making those trips, where those in dark blue recorded fewer than 100 trips in Bristol in the 31 month period and those in yellow recorded over 5,000 trips in the same time period. This graph shows that over a third (36%) of the trips made in the 12 months prior to the pandemic were made by fairly infrequent visitors, making fewer than 100 trips in the 31 month period. Even accounting for several months without trips due to lockdowns, this is still less than one trip per week on average. These types of visitors are likely to be making discretional trips, for example for leisure or non-grocery shopping, as only 20% of trips made in April 2020 were made by these infrequent travellers. The drop was even greater for those vehicles observed fewer than 10 times in the whole of the 31 month period, as they made 9% of all trips in the year prior to the pandemic, but only 2% of trips in April 2020. By the summer of 2021, however, the relative sizes of these different traveller types had returned to pre-pandemic levels.

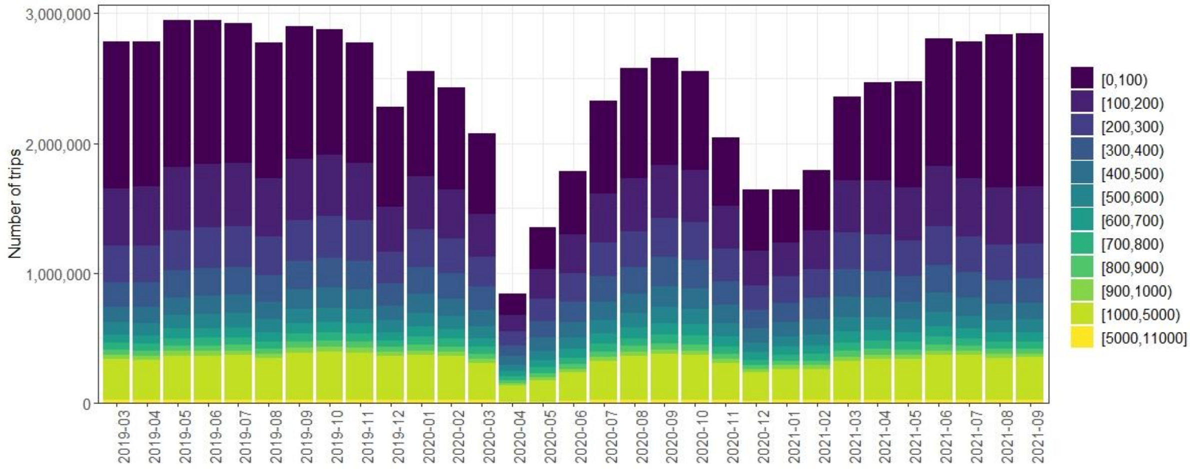

Figure 14: Monthly trips shaded according to the frequency of trips made by the vehicle

Figure 15 shows the same data but this time each bar is the same height so that the differences in percentages can be more easily observed. The decrease in the share of trips made by infrequent travellers was mostly balanced out by an increase in the share of trips made by vehicles observed making between 300 and 2000 trips in the 31 month period, as opposed to the most frequent trip makers.

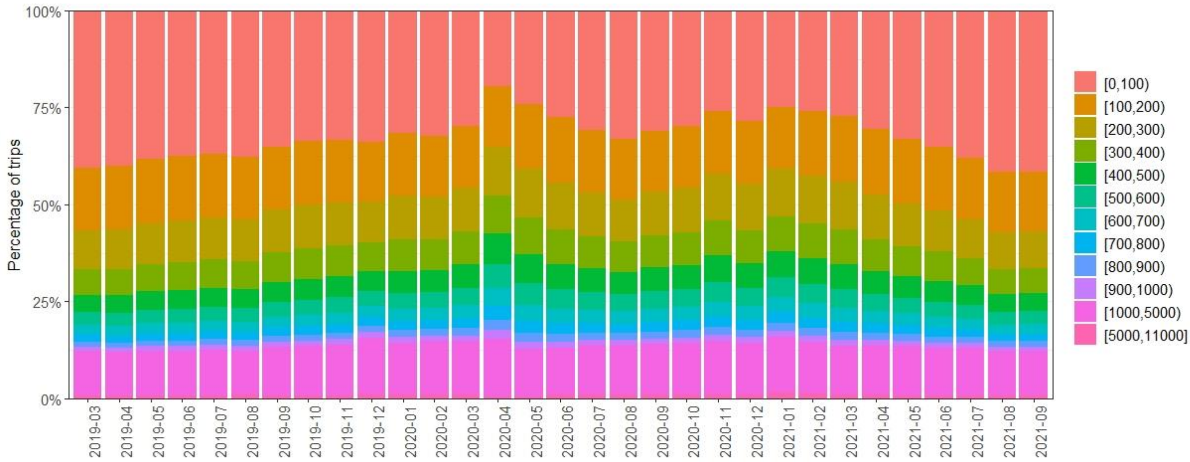

Figure 15: Percentage of trips each month according to the total number of trips recorded by the vehicle

4.3 Vehicles

Over 80% of the trips were made by cars and the second largest group was light goods vehicles (N1 type), which made 14% of the trips. Of the trips for which a fuel type could be identified, the vast majority (96%) were made in petrol or diesel vehicles. Over half of trips (53%) were made in diesel-only vehicles (i.e. excluding diesel hybrids).

Figure 16 shows how the percentage of trips by cars and light goods vehicles (LGVs) varied over time. LGVs made up 13% of trips in the year March 2019 to February 2020. The equivalent figure for 2020/21 was 16% which included peaks of 19% of trips in April and May 2020 and also in February 2021.

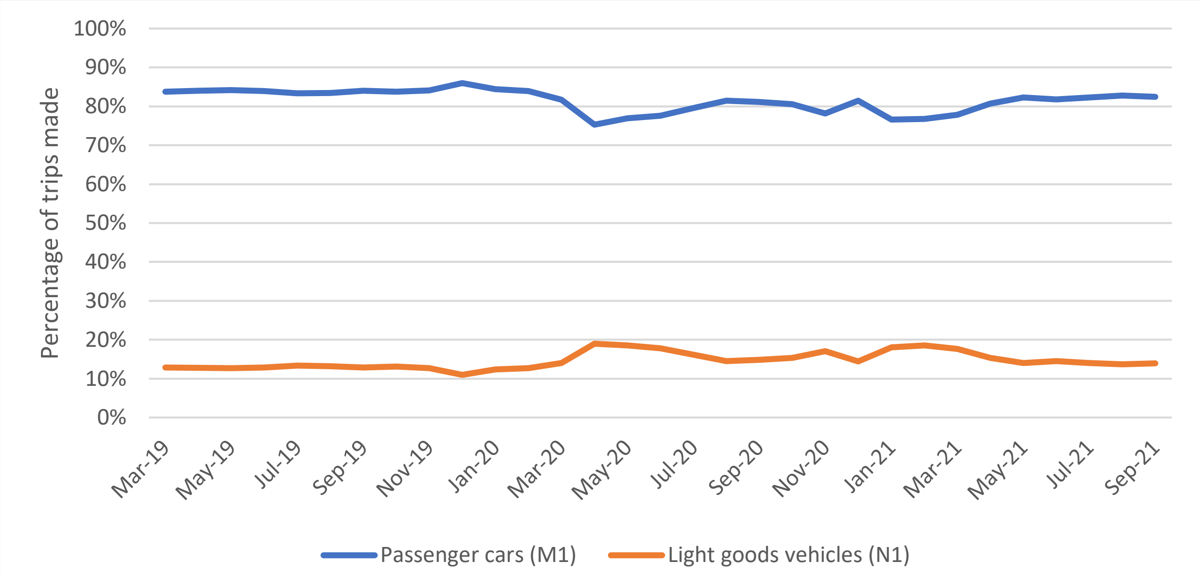

Figure 16: Percentage of trips per month by car and light goods vehicle

Buses and coaches (types M2 and M3) made up a slightly higher percentage of trips during the national lockdowns, but they still only made a very small number of the trips observed. In the year from 1/3/2019 to 29/2/2020, buses and coaches made 1.7% of trips, compared to 2.5% in following year. The peak percentage of trips by this type of vehicle was 3.2% of trips in January 2021. In Bristol, many buses run on gas and over the full analysis period, 31% of all M3 vehicle trips recorded were gas powered.

The DVLA data also provides the Euro Standard of some of the vehicles registered. In other cases, the Euro Standard can be estimated based on the type of vehicle, the date of first registration and the fuel type of the vehicle. Using this method, an estimate of the Euro Standard was made for vehicles making 84% of the trips in March 2019 to February 2020 and 88% of the trips in March 2020 to February 2021. Although the difference between the years is small, there could be a bias in that older vehicles may be less likely to still be registered in 2021 when the vehicle details were obtained from the DVLA database.

To obtain proper fleet estimates, it would be necessary to weight the data according to vehicle miles, as is done for the national estimates in the National Atmospheric Emissions

Inventory[8]. As this information is not available for the ANPR data, the Euro Standards are just weighted by the number of trips recorded by that vehicle in the given year, although this is a crude approximation for distance. The two years of data are compared in Table 1 and Table 2.

The data appears to show that whilst there has been little change in the Euro Standards of cars on the road in Bristol, there has been a shift towards newer LGVs and to a lesser extent HGVs.

Table 1: Estimated fleet composition based on Bristol ANPR data

	Year	Pre-Euro 4	Euro 4	Euro 5	Euro 6
Diesel cars	2019 - 20	4%	21%	38%	37%
	2020 - 21	4%	22%	38%	36%
Petrol cars	2019 - 20	10%	28%	27%	35%
	2020 - 21	9%	28%	27%	37%
Diesel small bus (M2)	2019 - 20	9%	26%	31%	33%
	2020 - 21	6%	28%	37%	28%
Diesel LGVs	2019 - 20	6%	15%	35%	44%
	2020 - 21	5%	13%	31%	51%
Petrol LGVs	2019 - 20	11%	18%	1%	70%
	2020 - 21	5%	9%	3%	83%

Table 2: Estimated HGV fleet composition based on Bristol ANPR data

	Year	Pre-Euro IV	Euro IV	Euro V	Euro VI
Diesel HGVs (N2)	2019 - 20	1%	5%	21%	74%
	2020 - 21	1%	3%	16%	80%
Diesel HGVs (N3)	2019 - 20	0%	3%	10%	87%
	2020 - 21	0%	2%	7%	91%

[8] https://naei.beis.gov.uk/data/ef-transport

4.4 Traveller behaviour

4.4.1 Geographic differences

As described in Section 3.2, time series clustering was undertaken on the monthly volumes of trips within each spatial cluster (i.e. group of spatially similar trips). A time series of monthly trips from March 2019 to September 2021 was calculated for each of the 47 spatial clusters. The clustering process identified two distinct groups of time series. These correspond to two different ways in which travel volumes were impacted by the pandemic, based on the geography of the trips.

The two distinct groups of time series are shown in Figure 17 and Figure 18. Figure 18 shows a representative profile for each of the clusters. Both profiles show the dramatic drop in trips in March 2020 followed by a gradual increase in trip making before a second fall in trips towards the end of 2020. The main difference between the two clusters is that trips-making returned to pre-pandemic levels during the summer of 2020 in cluster 2 and in some cases it exceeded pre-pandemic levels during the summer of 2021. Cluster 2 also saw a larger drop in trips during the first lockdown.

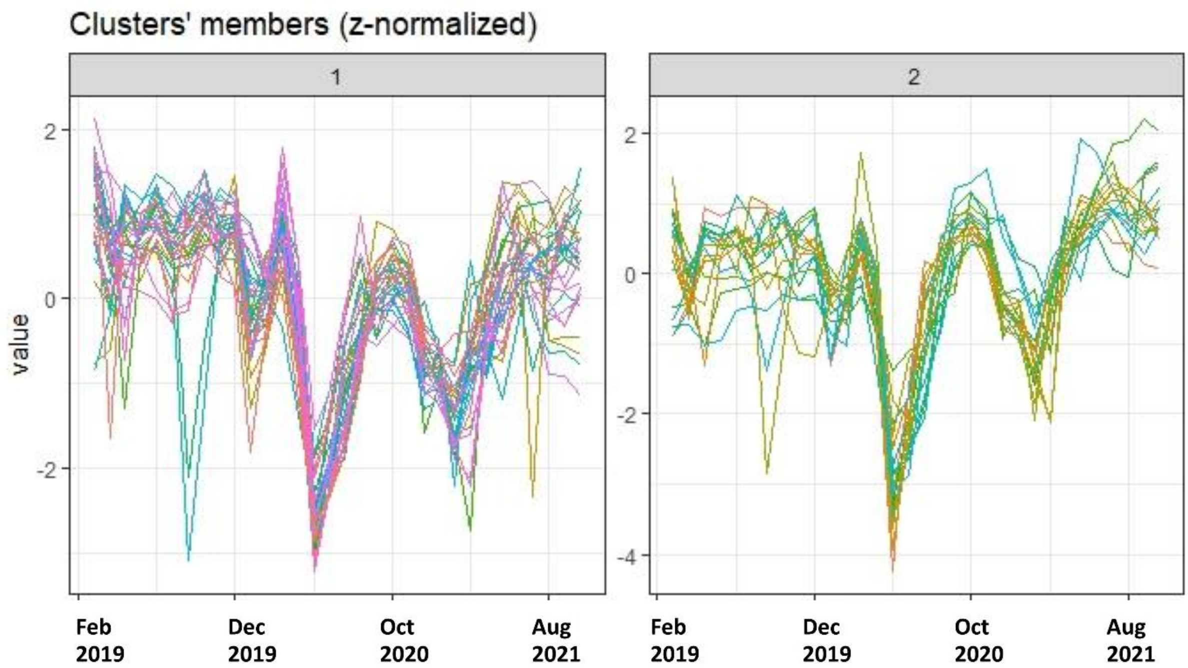

Figure 17: Normalised monthly trip counts from March 2019 to September 2021 for two clusters identified using Dynamic Time Warping

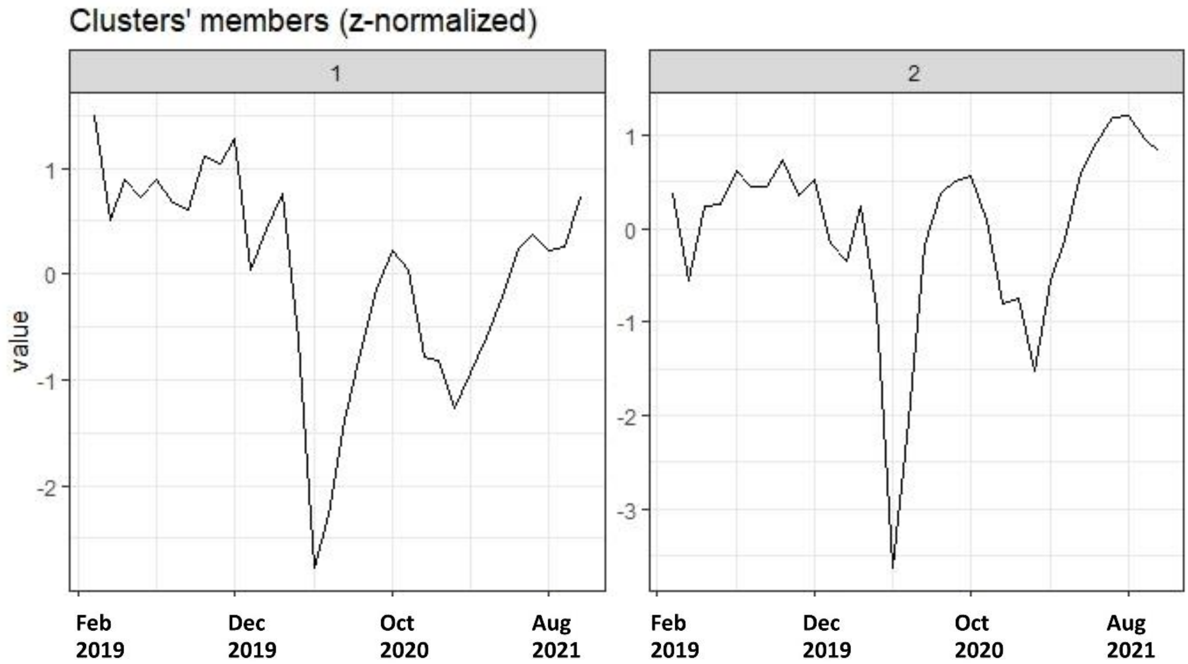

Figure 18: Centroid (representative) profiles for the two clusters identified using Dynamic Time Warping

The first cluster contains 30 of the 47 groups of spatially similar trips. The trips are not evenly distributed between these spatial groups, however, as 82% of the trips are associated with the first profile cluster. Figure 19 and Table 3 give an indication of the geographic differences between the time series clusters. Table 3 lists the most commonly observed trip sequence in the largest spatial groups assigned to each of the two time series clusters. The trip sequences associated with higher post-lockdown activity are located in the city centre or involve the route to the southeast of the city centre (via site L).

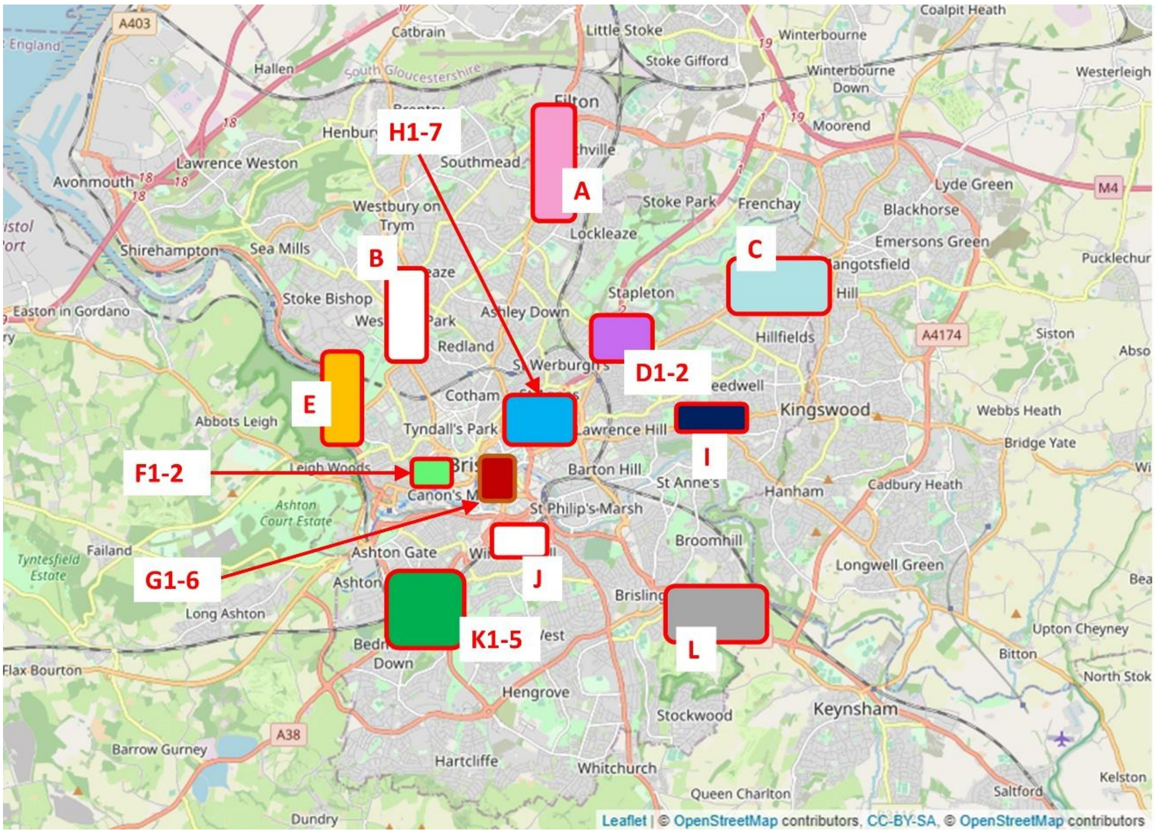

Figure 19: Colour-coded map of ANPR sites used in this report

Table 3: Most common trip sequence in the spatial clusters assigned to the two time-series clusters (spatial clusters with > 100k trips only)

DTW Cluster 1		DTW Cluster 2
H2 - H4	**K5 - G1 - H4**	**H3 - H2 - G5 - F1**
K4 - E	**A - D2**	**F1 - G5 - H2 - H4**
G2 - H4	**C - H3 - H2**	**I - H5 - H7**
F1 - H2 - H4	**H2 - H4 - C**	**G2 - L**
G5 - F1	**K3 - G1 - H4**	**H7 - H5 - L**
H3 - H2 - F2	**E - F1 - G5**	**K2 - L**
E - K2	**H3 - K1**	
H2 - I	**H3 - G1 - K1**	
H7 - H5 - I	**G5 - F1 - E**	
H2 - H4 - H5		

4.4.2 Frequent trip makers

As the examination of frequent trip makers should include vehicles which stopped making trips during the pandemic as well as vehicles which may only have appeared in the data since the start of the pandemic, the following rules were used to identify frequent travellers:

- At least 12 trips recorded in March 2019 to February 2020 or at least 6 trips recorded in December 2019 to February 2020 (for more recent vehicles)
- OR at least 12 trips recorded in April 2020 to September 2021.

March 2020 was not included in either group as it was a transition period including both pre-pandemic travel behaviour and, later in the month, national lockdown. Whilst once per month was considered to be a reasonable measure of frequent visitors in pre-pandemic times, this was relaxed to one trip every six weeks since the start of the first lockdown due to differences in trip making behaviour.

These criteria identified 525,683 vehicles which made a total of 65 million trips (16% of number plates but 87% of trips). Fewer of the frequently observed vehicles were cars (83%) compared to the less frequently observed vehicles (86%). This was balanced by a higher percentage of LGVs amongst the frequent vehicles (15%) compared to the less frequent vehicles (12%). Despite this difference in vehicle type, more of the frequently observed vehicles were fuelled by petrol (48% compared to 43% for non-frequent vehicles) and fewer were diesel vehicles. For the majority of vehicles, a Euro emissions standard was recorded by DVLA or could be estimated based on fuel and year of manufacture. For light-duty vehicles, 41% of frequently observed vehicles were Euro 6 standard compared to 49% of vehicles observed less frequently.

As described in Section 3.3, all trips made by these vehicles in April to June 2019 were collated and these were examined to identify the values of the following clustering variables for each vehicle:

1. The number of trips made.
2. The number of spatial clusters used.
3. The standard deviation of all trip start times in the 3 month period.

These variables were normalised and then were used to undertake k-means clustering of the vehicles. This process was undertaken independently on the trips in April to June 2020 and the trips in April to June 2021.

Despite being clustered independently, the trips in each year resulted in five clusters which had similar characteristics. This is likely to be as a result of the structural nature of trip making when considering this limited number of trip characteristics. For example, we might always expect to see occasional visitors, people who regularly shop in an area but do not do so more than once a week, frequent commuters and commercial vehicles making many trips. It should also be noted that the same group of vehicles was examined in each year and therefore the data is not independent between years.

Table 4 shows the number of vehicles in each of the clusters in each year. Figure 20 shows the same data as percentages. This plot shows that at an aggregate level, the number of vehicles in each cluster is fairly similar when considering 2019 and 2021 but that 45% of these regular travellers did not make any recorded trips in April to June 2020.

Table 5 shows the average value for each of the cluster variables in each year. This shows the non-linear relationship between the number of trips and the number of spatial clusters used. The average number of trips also varies between years for each cluster; whilst 2019 and 2021 are fairly similar, the 2020 clusters show slightly fewer trips on average and slightly fewer spatial clusters. Therefore, even if a vehicle remains in the same cluster between 2019 and 2020, it is likely that they made fewer trips and covered less of the ANPR network in 2020.

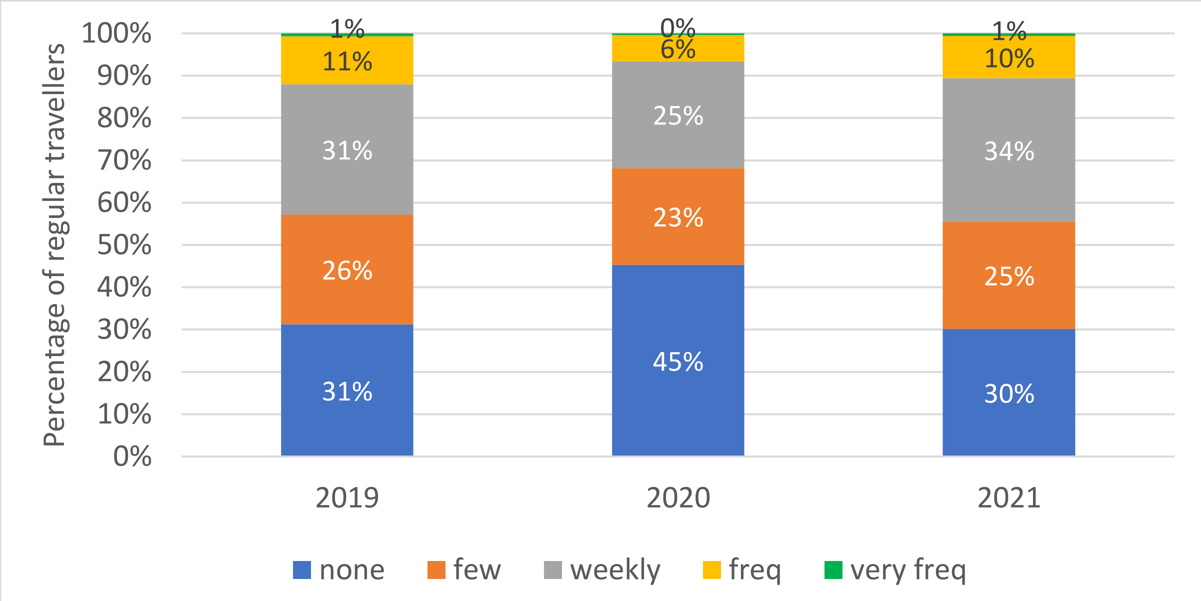

Figure 20: Cluster membership for trips made in April to June in 2019, 2020 and 2021 (consistent panel of 495,483 travellers/vehicles)

Table 4: Cluster membership for panel of frequently observed vehicles at three points in time

	Number of travellers (2019 clusters)	**Number of travellers (2020 clusters)**	**Number of travellers (2021 clusters)**
No trips	154,856	224,456	149,727
Few trips	128,470	113,388	125,047
Weekly trips	152,421	125,053	168,029
Frequent	56,390	30,850	49,501
Very frequent	3,346	1,736	3,179

Table 5: Average of clustering variables for the clusters identified at each point in time

	2019 clusters			**2020 clusters**			**2021 clusters**		
	Mean trips	Mean spatial clusters	Mean standard deviations of trip start times	Mean trips	Mean spatial clusters	Mean standard deviations of trip start times	Mean trips	Mean spatial clusters	Mean standard deviations of trip start times
No trips	0	0	N/A	0	0	N/A	0	0	N/A
Few trips	8	3	0.073	3	2	0.033	6	3	0.056
Weekly trips	15	5	0.199	11	4	0.158	14	5	0.176
Frequent	54	12	0.176	50	11	0.159	57	12	0.170
Very frequent	313	29	0.260	237	23	0.213	307	28	0.238

Additional vehicle data was used to examine the characteristics of the vehicles within each cluster in each year. Table 6 shows how the percentage of LGVs in each cluster varied between years. For the weekly, frequent and very frequent clusters, a higher percentage of members were LGVs in 2020 than in either 2019 or 2021. Whilst the 'very frequent' cluster is consistently the smallest cluster, it is notable that the percentage of LGVs in this group more than doubled between 2019 and 2020. By 2021, however, the LGV percentage in all clusters was similar to 2019.

As expected due to national fuel policies, the split between diesel and petrol vehicles shifted over the three years and a higher percentage of the vehicles making trips in 2021 were petrol compared to 2019. The drop in the percentage of diesel vehicles was greatest for the 'very frequent' cluster, where 79% of vehicles in this cluster in 2019 were diesel compared to 62% in 2021. This compares to a drop from 57% to 53% for the 'frequent' cluster.

Table 6: Percentage of cluster members which are light goods vehicles (N1)

Cluster	2019	2020	2021
No trips	18%	14%	16%
Few trips	15%	13%	15%
Weekly trips	10%	15%	12%
Frequent	21%	27%	23%
Very frequent	4%	11%	5%
Total	**15%**	**15%**	**15%**

Examining the overall number of vehicles in each cluster does not, however, tell us about how individual behaviour changed (or did not change). Figure 21 provides an indication of the individual transitions between different clusters in 2019 and 2020. This graph indicates the complexity of impacts of the pandemic as in each cluster the vehicles are split between those who remained in the same cluster, moved to a less frequent cluster or moved to a more frequent cluster. The ANPR data alone is not sufficient to be able to explain the different traveller responses, which could be driven by job type, industry, family circumstances and health conditions, amongst other factors.

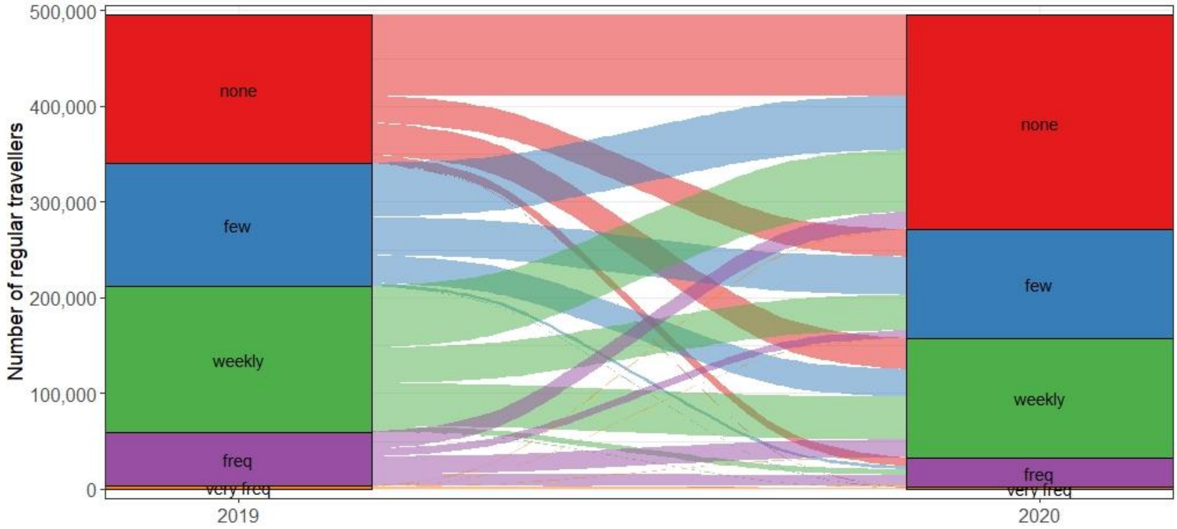

Figure 21: Transitions between clusters in April to June 2019 and clusters in April to June 2020

Care must be taken when interpreting membership of the cluster which recorded no trips. These vehicles may not be travelling into Bristol, for example due to working from home or a pause in deliveries to a retail establishment. However, many of the vehicles will not be making trips due to a natural churn in either vehicles or travellers, i.e. a turnover in the vehicles/people observed over time. For example, an individual or business may replace a vehicle with a newer model, or a person may obtain a new job which no longer requires them to travel into Bristol.

To examine the natural churn in vehicles in more normal times, ANPR trip data from the same sites in Bristol was compared for April-June 2018 and April-June 2019. Around 42% of vehicles observed in this period in 2018 were also observed in 2019. The total number of vehicles observed remained fairly stable, so a similar percentage of the vehicles observed in April-June 2019 had also been observed in April-June 2018. The percentage increases, however, for more frequently observed vehicles. Of the vehicles observed 3 or more times in April-June 2018 (i.e. once per month or more), 63% were also observed in the same 3 month period in 2019. For vehicles making at least 8 trips in the period in 2018, which is the average number of trips made in the 'few trips' cluster in the analysis of 2019 above, the reappearance rate was higher, with 73% also observed in the same period in 2019. This does not mean, however, that the vehicles were also observed travelling frequently in 2019. Depending on the definition of 'frequently observed' which is used, between 46% and 47% of frequently observed vehicles in April-June 2018 were also frequently observed in April-June 2019.

Figure 22 shows the transitions in individual cluster membership between 2019 and 2021. Again, there are a large number of transitions although many of them relate to transitions to or from the ‘no trips’ cluster which could indicate a vehicle was replaced or that an individual has chosen not to travel to Bristol anymore. Further research should be undertaken to identify the nature of ‘new’ vehicles in the area, particularly whether they are replacing existing vehicles or whether they represent a new demand for trips.

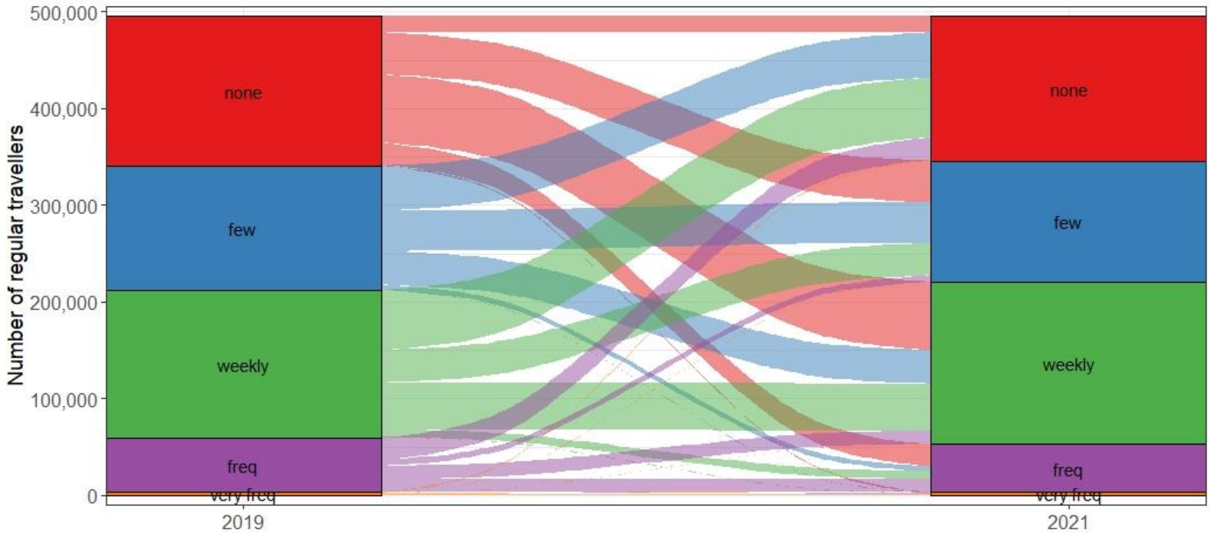

Figure 22: Sankey diagram of traveller types in April to June 2019 compared to the same period in 2021

Due to the relatively high turnover of vehicles, travellers who made trips in both April-June 2019 and April-June 2021 were examined in detail to determine how their behaviour has changed. Care should be taken in interpreting the results for this subset as they ignore new vehicles in the area specifically generated by the pandemic, for example an increase in supermarket delivery vans, as well as travellers who have not yet resumed their pre-pandemic activities.

After excluding all regular travellers who were in the ‘no trips’ cluster in 2019 and/or 2021, 208,216 travellers remained (42% of the regular travellers). Of this subset, 36% remained in the same cluster from 2019 to 2020, 14% moved to a higher frequency cluster and half moved to a cluster representing less frequent trip making. If we compare 2019 to 2021, however, a slightly different picture emerges as 50% of the travellers are in the same cluster as they were prior to the pandemic and the remainder are fairly evenly split between those in a more frequent cluster (23%) and those in a less frequent cluster (26%). It should be noted, however, that the cluster definitions vary slightly across years and there is within group variability, so travellers are not necessarily making the same number of trips if they have remained within the same cluster.

There were also differences according to vehicle type as 19% of those making more trips in 2020 than 2019 were LGVs compared to 10% of those who were making fewer trips. LGVs also featured more prominently in the vehicles which had increased trip frequency between 2019 and 2021 although the difference was far smaller than when we consider the data from the first national lockdown.

5 Discussion

Whilst the analysis presented in this report relates to Bristol only, the methodology can be applied in other locations. The identification of two distinct clusters of time series (using the Dynamic Time Warping process) when considering trip sequences highlights the need to look at the impact of the pandemic in terms of origin-destination (OD) pairs rather than volumes at a specific site or at area-wide level. Future work could look at OD matrices from local transport models to see whether further insights can be obtained by identifying the OD pairs which include the relevant ANPR trip sequences. For example, Staff at Bristol City Council suggested that it would be useful to examine whether one of the clusters of time series might be more closely related to trips entering the city centre via the strategic road network.

One of the challenges in exploring the impact of the pandemic is that transport infrastructure and travel behaviour are not static. In this report we have considered the rate of 'churn' of vehicles on the roads in Bristol in more typical times and the natural evolution of the vehicle fleet should be considered alongside 'pandemic' changes. More localised effects will also be present, however. For example, when we consider the trip sequences which have exceeded pre-pandemic volumes in mid-2021, are these due to changes in the places people are visiting or is this a result of improvements in local infrastructure? The ANPR data examined was not of sufficiently high resolution to be able to examine whether increases in volumes on certain routes was due to new trips or changes in route choice.

Whilst most of the aggregate level data shows that trips in Bristol were similar to pre-pandemic trips by the summer of 2021, the individual vehicle analysis suggests that individual trip-making has not returned to previous patterns in many cases. Around half of the vehicles observed in the spring of 2019 and in the spring of 2021 had roughly similar frequency of travel in the two periods. The remaining vehicles were evenly split between those travelling more frequently and those travelling less frequently. This has implications for air pollution since LGVs are more likely to now be travelling more frequently. Further research is required to understand other equity implications of the shift in behaviour. For example, are higher income workers more likely to be able to work from home and therefore avoid areas of higher air pollution in city centres?

The increase in trips by LGVs during the national lockdowns is of particular interest as it demonstrates how policies to encourage people to reduce their personal motorised travel can have unintended consequences. More efficient and sustainable methods of transporting goods to businesses and households, particularly in urban areas, will be key to achieving real improvements in air quality.

In considering the research findings it is important to keep in mind the limitations of the data. Whilst the cameras offer good coverage of the main roads into the city, they were placed to capture the core movements within the city pre-pandemic. Staff from the Traffic Control Service reported a shift towards more traffic on local streets and in residential areas as lockdowns were lifted. It is therefore important to ensure that we continue to adapt data collection strategies to adapt to changing travel patterns.

6 Conclusions

The ANPR data provides a useful snapshot of behaviour before the pandemic and in the year and half since the first lockdown, but the insights are insufficient to be able to predict future behaviour. It is unclear whether travellers who have reduced the number of trips they make by road in Bristol between 2019 and 2021 have made a permanent change or whether this group will gradually return to the city as vaccination and booster rates continue to increase.

Whilst the first national lockdown caused an unprecedented drop in traffic volumes, by the summer of 2021 at the latest, traffic volumes had returned to pre-pandemic levels. The pandemic may not have a substantial, lasting effect on air quality directly, but by exploring how people adapted during this time of crisis and by utilising the technological and cultural changes resulting from the lockdowns, perhaps more effective policies for improving air quality can be devised.

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