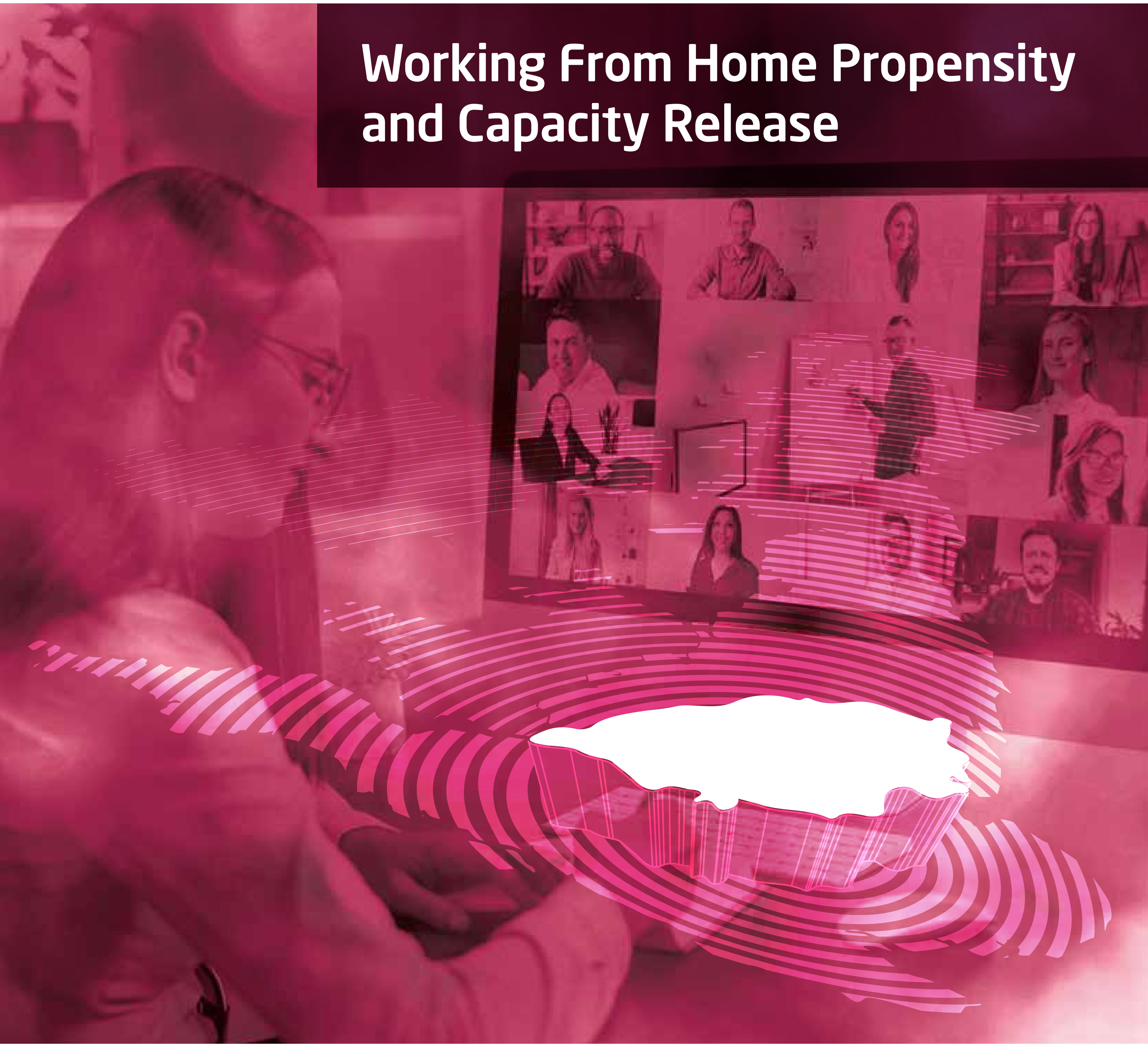
ENGLAND'S ECONOMIC HEARTLAND

# Working From Home Propensity and Capacity Release



A technical report produced by City Science for the EEH evidence base

# Contents

# 1 Executive Summary

1.1.1 This project has developed a model that can be used to explore different future scenarios of Working-from-Home. The model applies the effects geospatially based on detailed geodemographic data. The effects can then be routed through a network to translate these demand effects into potential traffic and capacity release impacts along key corridors or routes.

1.1.2 Our model predicts that if people who used to commute by car and who are now working from home were to continue to do so for two days per week, between 10% to 12% of peak hour traffic would be removed. This is consistent with independent findings from the University of Leeds who estimate that this level of home working would reduce morning car trips by 14%.

1.1.3 This level of working from home has the potential to have significant impacts on the road network. To analyse this we applied a 25%-COVID scenario (roughly equivalent to ~1.25 days working from home) to the baseline demand provided. While this scenario results in only a 6% reduction in total peak hour travel, the model predicts that most roads would experience traffic reductions in the region of 3%-10%. Localised impacts are expected to differ due to the precise make-up of resident demographics and sector-mix in the economy and the speed-flow characteristics of specific roads.

1.1.4 The model was also applied to a calibrated base-year transport model for a subset of the EEH network around the Peterborough area. Broadly speaking this confirmed the overall picture with reduced flows predicted in 90% of links. However, it also confirmed the likelihood of localised differences and difficulty making a direct read-across from demand to flows without a model.

1.1.5 **Next Steps:** The modelled outputs will be made available for the purposes of further analysis within the corridor studies. This will include two forms of demand matrices – both in agent-based form for integration with the EEH Policy tool, and in traditional form for analysis of travel desire lines along the key corridors.

# 2 Introduction

2.1.1 It is no exaggeration to say that the events of 2020 have created significant challenges for future transport planning exercises. Even before the pandemic, transport modellers were increasingly questioning how models could be adapted to better accommodate uncertainty. But the Covid-19 pandemic has taken modelling uncertainty to new extremes, introducing new transport trends that are confounding future transport predictions and models including:

- A very substantial increase in the number of people working from home.
- A significant short-term decrease in the number of people using public transport.
- An acceleration of digital purchasing behaviours and
- Long-term changes in preference that could result in long-term changes in land-use.

2.1.2 While some of these changes, such as the use of public transport, may normalise over time to something close to pre-covid levels, other changes, such as the increase in working from home, have the potential to become a permanent fixture of the transport landscape - albeit to a lesser extent than we have seen during the pandemic's peak.

2.1.3 Substantial shifts in commuting behaviour offer the potential opportunity to explore alternatives to traditional investments aimed at mitigating peak-hour congestion. However, to identify where such reprioritisation might be beneficial, it is critical to be able to predict both changes in propensity for home working and how these translate into changes in transport infrastructure capacity.

## 2.2 Project Background

2.2.1 England's Economic Heartland has adopted an ambitious transport strategy which seeks to deliver net zero emissions by as early as 2040 while supporting economic growth. The strategy makes clear that enabling growth in a way that improves the environment requires a fundamental switch in the way the region's transport system is planned and delivered. One of the strategy's key policies is to champion digital technologies to make transport smarter.

2.2.2 City Science developed an England-wide model that can predict the propensity for working from home, based on a number of factors like occupation income, household size and digital connectivity etc. The goal of the current project is to enhance and apply the model to the EEH area and use it to produce outputs that can feed into the EEH corridor studies.

2.2.3 EEH's current work includes a programme of connectivity studies which will identify solutions for improving the transport system in a number of corridors across the region, starting with Oxford-Milton Keynes; and Oxfordshire-Northamptonshire-Peterborough. Understanding the potential for home working and capacity release will be essential to support the planning for these corridors, potentially reducing requirements for high cost, high carbon infrastructure and identifying areas which would benefit from expenditure in digital infrastructure.

## 2.3 Related Literature

2.3.1 Our study coincided with the release of an independent study from CREDS which provides additional context that we refer to throughout this report. The CREDS study is based on independent surveys and analysis undertaken by the University of Leeds. The key findings of this study are as follows:

- Prior to the pandemic just over 25% of the workforce had some experience of working from home with around 12% of the workforce working at home at least once per week. During the pandemic the number of days working from home quadrupled.
- The extent to which the population can work from home varies both across occupation and role. This translates into differences by area reflecting the structural differences in local job markets. Financial Services, IT, Media/Marketing, Professional Services, Real Estate and Government/Public Sector are most likely to have experienced the biggest increases in home working.
- Nationally occupations more likely to use the car for commuting were most likely to be those continuing to commute by car to work. Switchers to working from home were more likely to be public transport users than car drivers and, of those, they were more likely to make bigger switches if they were previously rail users.
- Those who continue to never work from home are disproportionately reliant on the car for commuting and make up the majority of the working population.
- ~25% of survey respondents said they would work from home a little or much more in the future with ~23% saying they would conduct business meetings online to replace business travel.
- Changes to LGV and car traffic through the COVID-19 pandemic have tracked each other with a near-linear relationship, while changes to HGV traffic has been more difficult to predict.
- **The study estimates that continued working from home for two days per week would translate into a reduction of morning car commuting trips of 14%.** As we will see, this finding is replicated independently through our model and analysis.

2.3.2 Prior to the COVID-19 pandemic there had also been some research on the impacts of 'telecommuting'. While many studies identify the potential benefits from reduced commuting, the literature notes that other factors may reduce the overall carbon benefits if unmanaged – for example, impacts of increases in home energy consumption or unpredictable increases in non-work travel. Another concern cited is that tele-workers may be more inclined to accept a job that further away from home if they have the ability to work from home one day a week or more (de Vos, 2018). With studies suggesting possible increased distances of between 2.3-10.7 miles, if uncontrolled, longer-term land-use effects could therefore induce sprawl and result in higher carbon for non-commuting journeys (Helminen, 2007; De Abreu, 2017). It is therefore important to consider and mitigate against other unintended consequences of increased home working.

# 3 Methodology

## 3.1 Data Sources

3.1.1 The WFH propensity model uses three broad categories of data:

1. **Model-building data:** This includes data required to build a nation-wide model of digital propensity (in addition to the data used to build the transport demand and assignment models);

2. **Model-linking data:** This includes data required to link that model to the EEH area at the level of Lower Super Output Area (LSOA);

3. **Cross-reference data:** This includes data on fixed-line broadband coverage at LSOA level to cross-reference with data from the WFH propensity model.

3.1.2 Table 1 lists all the data sources used categorised by these headings.

| Model building data |
|---|
| **Understanding Society Covid-19** – The Understanding Society COVID-19 Study is a regular survey of households in the UK. The aim of the study is to enable research on the socio-economic and health consequences of the COVID-19 pandemic, in the short and long term. The surveys started in April 2020 and took place monthly until July 2020. From September 2020 they take place every other month. They complement the annual interviews in the Understanding Society study. Critically the survey contains questions on working from home pre- and post- covid, which allows it to be used to build predictive models of propensity to work from home before and after covid-19. This data was accessed from the UK data service https://www.ukdataservice.ac.uk |
| Model linking data |
| **Business Register and Employment Survey (BRES)** - BRES publishes employee and employment estimates at detailed geographical and industrial levels. BRES is regarded as the definitive official government source of employee statistics by industry. This data was accessed via NOMIS https://www.nomisweb.co.uk |
| **Annual Survey of Hours and Earnings -** The Annual Survey of Hours and Earnings (ASHE) is based on a 1% sample of employee jobs taken from HM Revenue and Customs PAYE records. This data was accessed via the ONS https://www.ons.gov.uk/employmentandlabourmarket |
| **Census data on employment status –** Data at MSOA level on the percentage of people working full- or part-time or self-employed. This data was accessed via NOMIS https://www.nomisweb.co.uk |
| **Baseline demand matrix –** The baseline demand was drawn from an agent-based demand model supplied by Immense for the EEH area consisting of approximately 10 million trips. The demand model represents trips made during an average weekday in 2016. This represents trips starting, ending and travelling through and between regions surrounding the EEH area. |
| Cross-reference data |
| **Broadband fixed line coverage by postcode –** data collected by OFCOM detailing level of broadband coverage available at postcode locations. This data was accessed from: https://www.ofcom.org.uk/research-and-data/multi-sector-research/infrastructure-research/connected-nations-2015/downloads |

| |
|---|
| **Link between 2011 area codes and postcodes –** Links between postcodes and 2011 census area codes. Accessed from https://geoportal.statistics.gov.uk/ |

*Table 1: Data Sources*

3.1.3 Due to the availability of data at different stages of the project, two methods have been applied to link the national model to zones within the EEH. An overview of each method and the data it uses is set out below. Method 1 is the preferred method since it enables linking to non-employment attributes of different zones, however data approvals and licensing are more restrictive. To overcome this problem we used method 1 to generate a table of WFH probabilities at lsoa level, which can then be applied without restriction anywhere in England or Wales. The second method can be applied using open data and is therefore more replicable, but it is not the preferred method because it relies on the assumption that the distribution of model predictors among agents within an area is independent. In the real world this assumption is violated resulting in a bias towards overestimating the propensity to work from home. In what follows we present results for the preferred method (method 1).

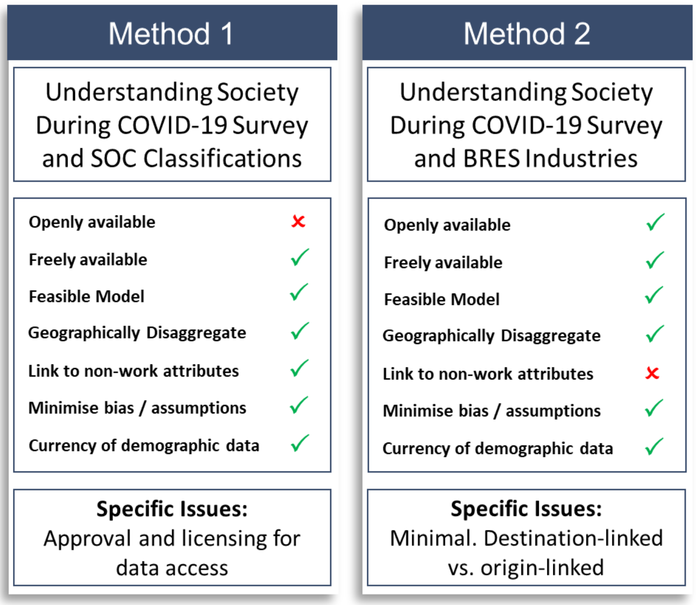



*Figure 1: Data sources and linking methods used*

## 3.2 EEH Policy Tool

3.2.1 EEH uses a transport policy planning tool based on an agent-based simulation developed by Immense. This project was designed to link with the EEH Policy tool at two levels:

1. **Baseline Demand:** Using the same agent-based baseline demand from the policy tool;
2. **Integration:** Delivering outputs in a format suitable to integrate with the policy tool.

3.2.2 To achieve this, our model has been designed to supply revised demand matrices in an agent-based format for use within the Policy Tool.

## 3.3 Propensity Model

3.3.1 The Working from Home (WFH) propensity model was developed by City Science using data from a national survey known as Understanding Society Covid-19 (USC19). This longitudinal survey was conducted monthly from April 2020 and included data on people's choice of how frequently they worked from home both before and during the pandemic (Figure 2). From this it is clear that there was a very substantial increase (~30%) in the percentage of people working from home all or most of the time as a result of the pandemic.

3.3.2 Moreover, Figure 2 demonstrates that the step-change in working from home observed following the first lockdown, was not significantly reduced as lockdown restrictions relaxed.

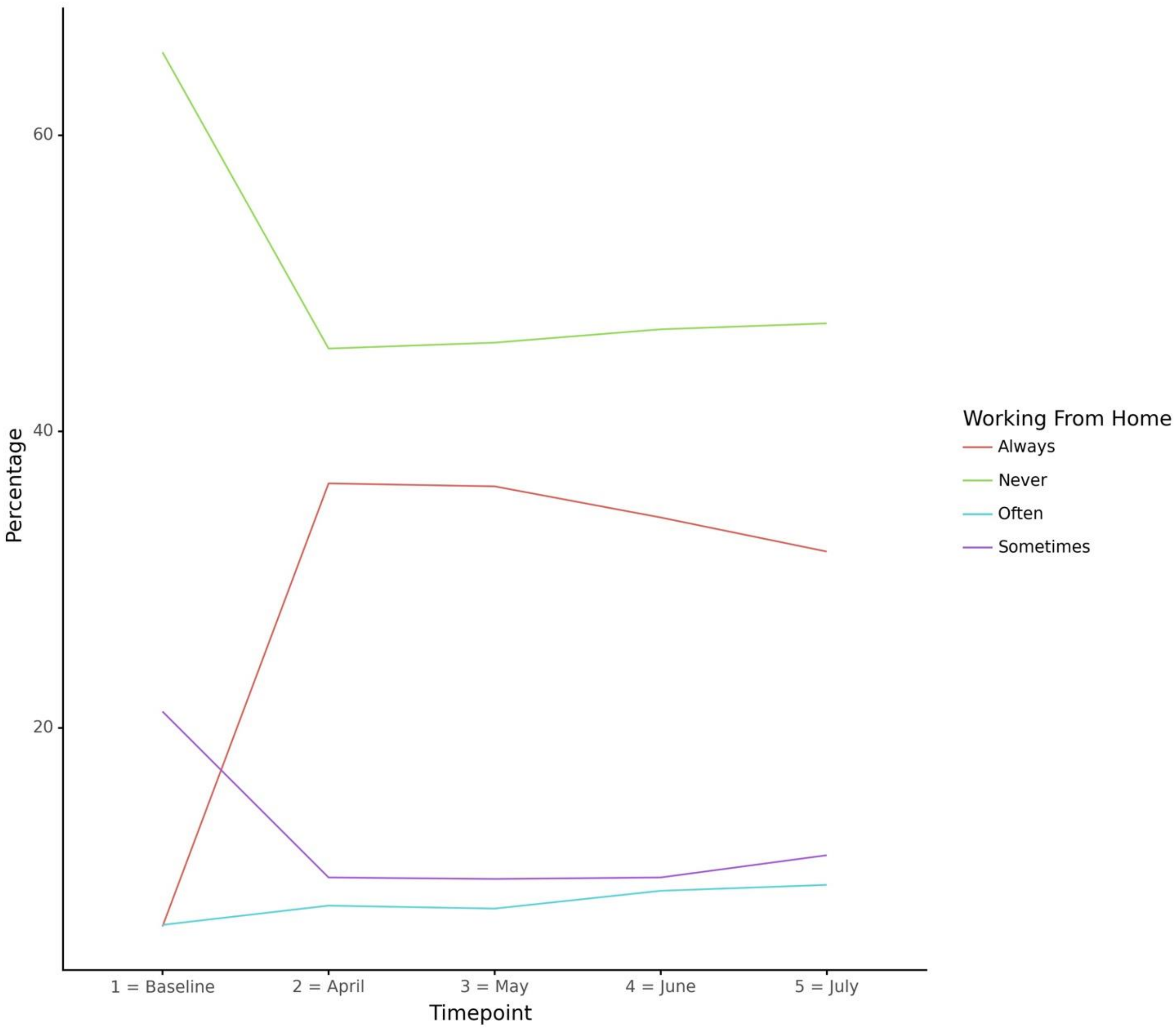



*Figure 2: National change in working from home as a result of COVID-19*

3.3.3 This reflects similar findings from CREDS (captured in an independent survey) who found that prior to the pandemic just over 25% of the workforce had some experience of working from home and that, as a result of the pandemic, the total number of days worked from home quadrupled (Marsden, 2021).

3.3.4 We used this data to build two national models of propensity to work from home for the periods before and after lockdown. The models were created using a mixed modelling technique with potential fixed predictors selected from appropriate variables within the USC19 dataset. Predictors were selected for inclusion in the models using a backwards/forwards technique where variables were added and then removed incrementally until optimum model performance was reached (judged on the Akaike information criterion (AIC) , which penalises overly complex models).

3.3.5 Geographical location was used as a random variable to cater for the likely possibility that there would be other geographically distributed predictors of propensity to work from home that would not be available within the USC19 dataset.

3.3.6 Figures 3a and 3b show the national model coefficents for the pre and post-covid models respectively, with black lines indicating the 95% confidence intervals. Figure 3c shows the two model predictions for a sample of the USC19 data colour coded by self-employment status.

3.3.7 It is striking that in the pre-COVID case, self-employment was a major predictor of working from home; whereas post-COVID the distinction between self-employed and employed all but disappears. People in highly-paid jobs working in business, public service or IT professions are most likely to work from home post-COVID. However, some occupations remain very unlikely to be working from home (e.g. transportation or hospitality) - presumably because in these cases it is physically impossible.

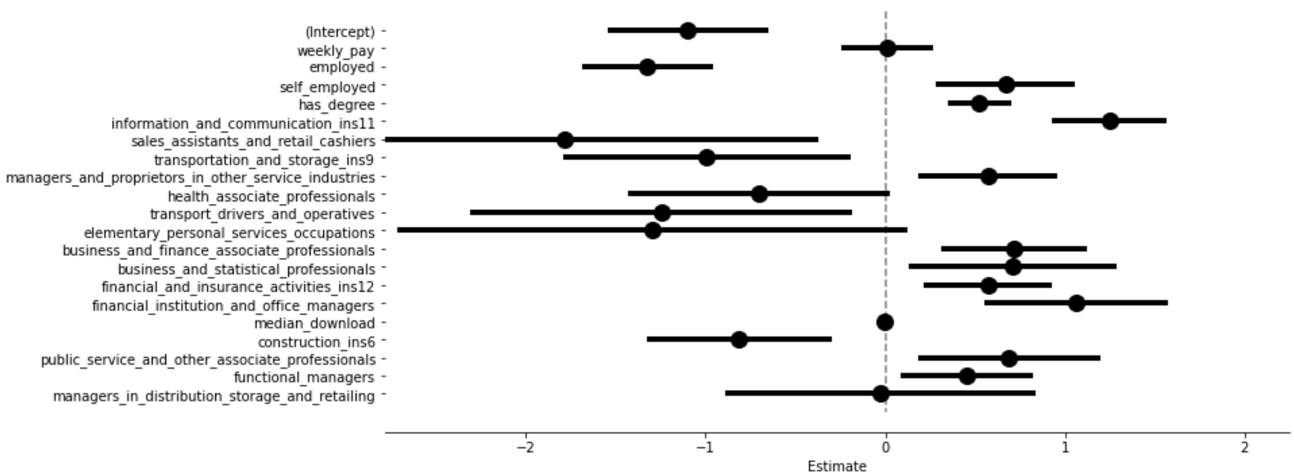



*Figure 3a: Model coefficients pre-COVID*

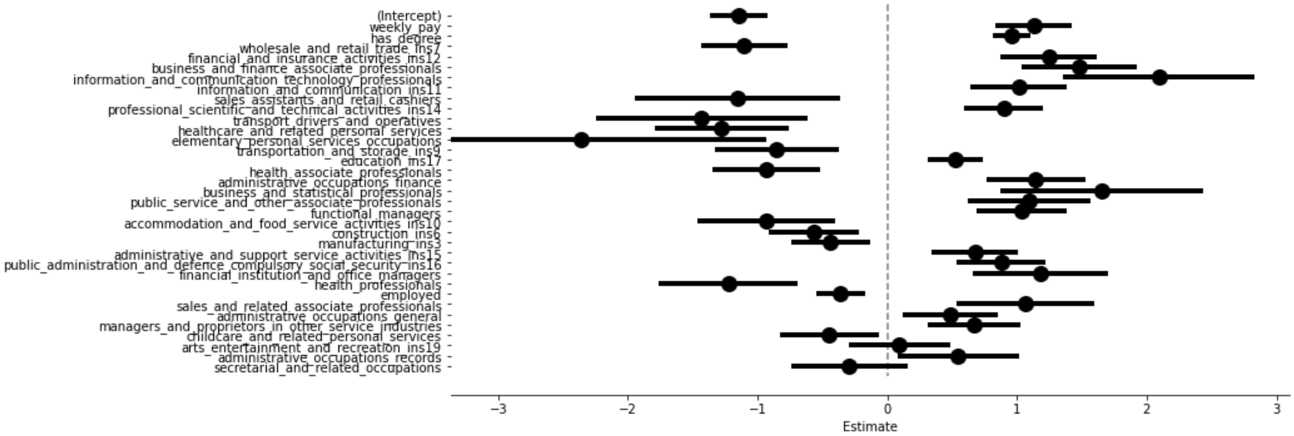



*Figure 3b: Model coefficients post-COVID*

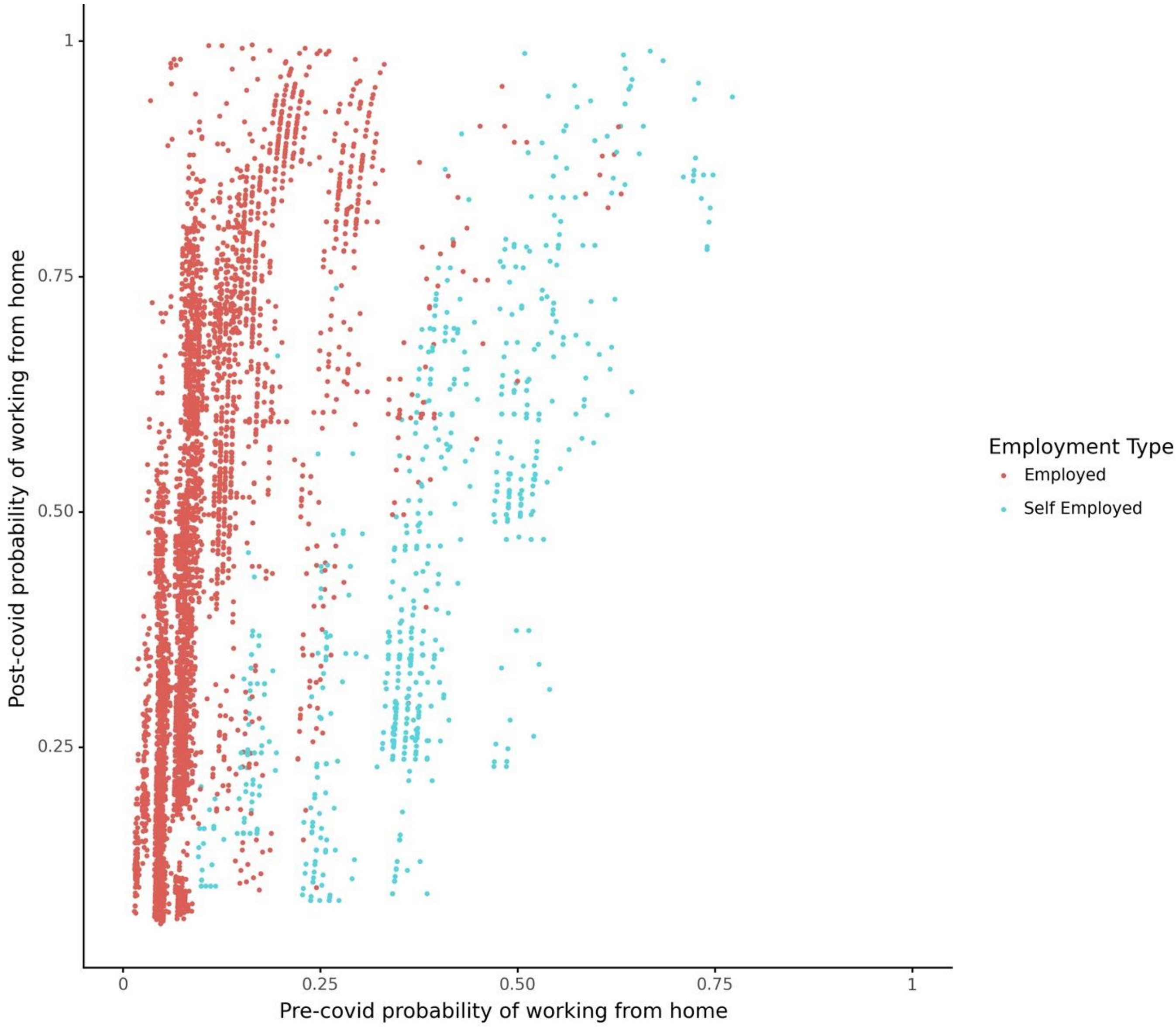



*Figure 3c: Pre- and post- COVID model predictions categorised by employment status*

## 3.4 Analysis Methods

3.4.1 For method 1 the digital propensity model was linked to the EEH geography by using the model to predict the probability of working from home at the level of LSOA and then averaging these predictions across LADs. For method 2 demographic data at the level of Lower Super Output Area (LSOA) or Middle Super Output Area (MSOA) was used to generate pseudo-characteristics for each of the 'agents' within the baseline demand model. The digital propensity model was then used to predict the probability that each of these agents would be working from home both before and after COVID. In both cases the predicted probabilities were then used to calculate the probability that the commuting journeys in the baseline would no longer have occurred post COVID according to the following formula:

$$P_{delete} = \ Band \times \frac{1 - P_{wfh-post}}{1 - P_{wfh-pre}}$$

Where:
$P_{delete}$ is the probability that the baseline commuting journey will be deleted.
$P_{wfh-post}$ is the probability of an agent working from home post-COVID.
$P_{wfh-pre}$ is the probability of an agent working from home pre-COVID.
$Band$ is a scenario factor indicating what percentage of the post-COVID reduction in traffic demand is applied.

## 3.5 Limitations

3.5.1 The solution has a number of limitations which are listed below, categorised into two groups: 1) limitations of the propensity model itself, and 2) limitations of application that should be bourn in mind when interpreting results.

3.5.2 **Limitations of the Propensity Model:**

- **WFH-Only:** The model focuses on working from home propensity as it relates to previous commuting traffic. While this is expected to be the major long-term effect relevant to demand, the model does not account for other potential COVID-related effects. For example, the model does not account for changes to HGV traffic which have been observed not to mirror changes to car traffic (Marsden, 2021), nor does the model capture potential changes to other journey purposes (for example increased or decreased leisure activity). The model also does not distinguish between users based on their previous mode (all pre- and post-COVID flows are car-based). Recall that CREDS found that switchers to working from home were more likely to have previously been rail users than car drivers – further differences in behavioural responses to mode choice not fully captured by this approach, may play out as we emerge from the pandemic.
- **Weekly patterns:** The model assumes equivalence across weekdays and does not account for the potential for new behavioural patterns to emerge e.g. a pick up in "social commuting" on specific weekdays.
- **Long-term land-use effects:** The model does not include potential future land-use effects such as those referenced in pre-COVID studies on telecommuting (see section

2.3.2). While CREDS' survey data shows no greater tendency for people who work from home to say they have an increased desire to move home (Marsden, 2021), the long-term effects on migration patterns are as yet unknown (potential land-use effects are only starting to be considered in academia, for example see Batty/CASA working paper 226).

- Stochastic Process: The process of replacing selected previous commuting journeys with WFH is stochastic and so it is possible that another run of the same process would give different results. To mitigate against this, we produced two runs with different random seeds. This demonstrates that at the level of overall traffic flow the tested scenarios are indistinguishable.
- Regional Differences in Response: The digital propensity model was developed based on data that was representative of the UK population as a whole, including samples from the EEH area. This means that the model should be able to deal with regional variations in the EEH area due to concentrations of particular industries. However, if the effect of the factors in the model are different within the EEH area to the UK as a whole than this would not appear in the modelled results. For instance the model suggests that people working in IT are very likely to work from home. If EEH has a higher concentration of professional IT workers than this will be captured by the model, but if there was a large IT employer within EEH with a policy of not allowing home working at all than the model would not not reflect this kind of regional variation.

### 3.5.3 Limitations in the Application:

- Input Demand Model: While the propensity model uses survey-data captured through the COVID-19 pandemic, the outputs are applied to the baseline demand model supplied through the policy tool. In this sense the accuracy of the EEH predictions have a dependency on the baseline demand supplied. This baseline model is derived from demand data gathered in 2016 and no Local Model Validation Report for the baseline has been reviewed.
- Demographic Model: In Method 2, the pseudo-characteristics generated for each agent in the baseline are generated assuming that each characteristic is distributed independently of all other characteristics – this is likely an over-simplification. Method 1 does not suffer from this limitation.
- Assignment: For illustrative purposes (to help picture the potential impacts on peak-hour road capacity), we have assigned the pre- and post-COVID matrices to an EEH road network. **This provides a helpful visualisation to understand potential impacts on the network overall, but changes to specific link-flows should be used with caution.** Since, the baseline assignment is not calibrated to pre-COVID flows, routing behaviour to specific links could be considerably different. To illustrate this point we applied the model to a calibrated demand matrix for the Peterborough area. This resulted in a similar pattern of flow reductions, but an overall diminution in the degree of predicted flow reduction. Further work would be required to understand the origins of these differences.

# 4 Scenarios

4.1.1 Behavoiur change during the peak of the COVID-19 pandemic represents the most extreme reduction in traffic possible when everyone who can work from home does so. To cater for the likelihood that the long-term increase in working from home will be less than this, we created four different illustrative scenarios:

1. No reduction in traffic
2. A reduction equivalent to that seen during the COVID-19 pandemic (May and June 2020). This scenario is described as the “full post-COVID” scenario.
3. A reduction equivalent to 50% of the post-covid reduction (or continued home working for ~2.5 days per week).
4. A reduction equivalent to 25% of the post-covid reduction (continued home working for ~1.25 days per week). This scenario is described as the “25% COVID” scenario.

4.1.2 The next section discusses the results for each of these scenarios.

# 5 Results

## 5.1 Changes to Demand

5.1.1 Figure 4 shows the overall reduction in number of journeys within the EEH area expressed as a percentage of the baseline.  When applying all the modelled reduction observed in the post-covid period, the number of overall total journeys drops to 85% of the baseline.  If we assume only 25% of the covid-related reduction (25% COVID scenario) then the number of journeys drops to 96% of the baseline. When considering these figures it is important to bear in mind that this reduction is expressed as a percentage of all journeys across the whole day and not just commuting journeys at peak times.

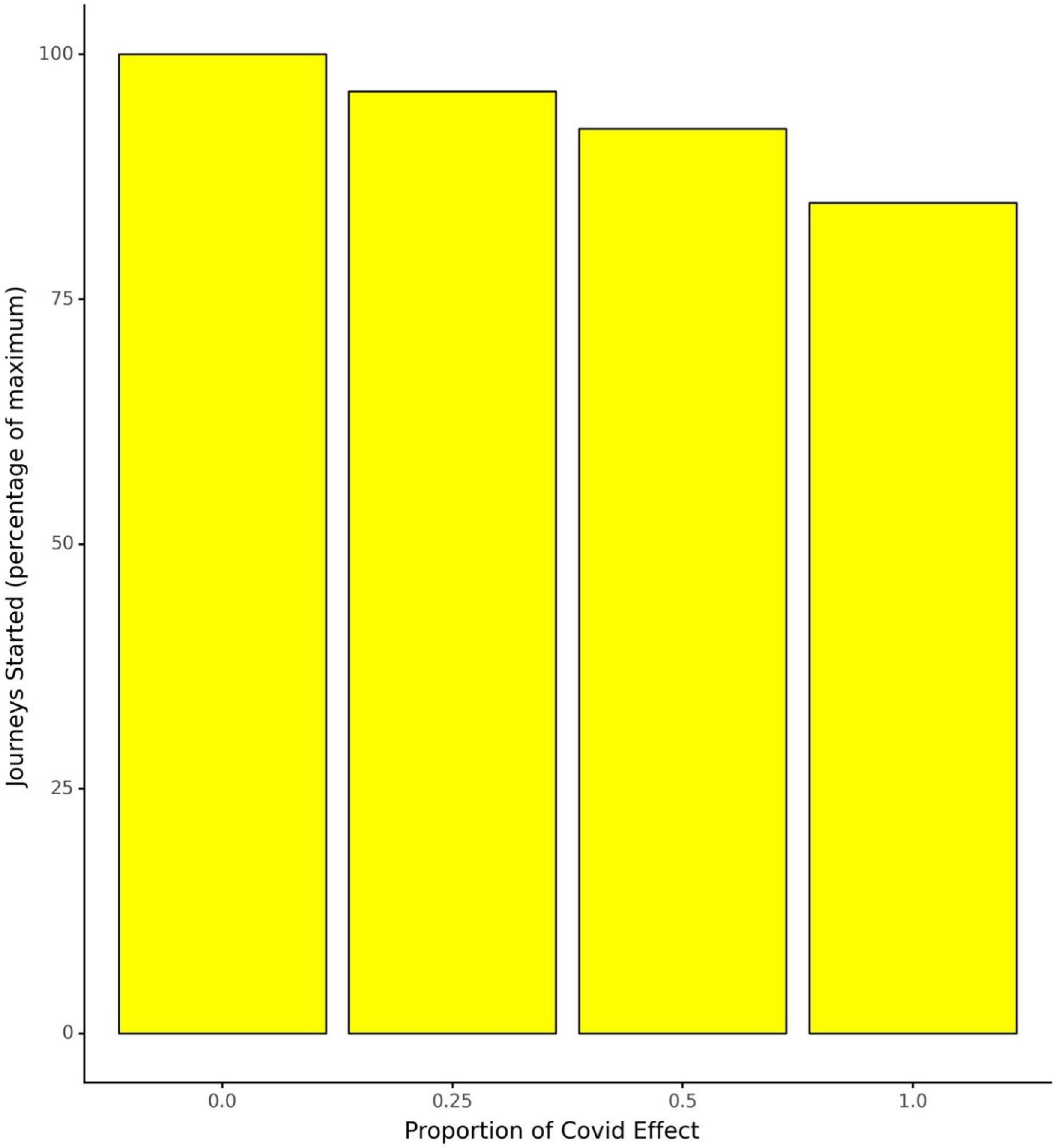



*Figure 4:  Changes in overall travel demand within the EEH area as a result of increased WFH*

## 5.2 Changes to Peak-Hour Demand

5.2.1 Of course, traffic demand is not evenly spread across the day so it is important to look at how the predicted increases in working from home would be expected to affect peak demand. This is illustrated in Figure 5, which shows the number of journeys commencing each hour under each of the four scenarios. It is clear from this that the effect of even a relatively modest increase in propensity to work from home is magnified when it comes to reducing peak-hour demand. If the full 100% COVID reduction is modelled, then we would expect the peak demand to drop by 24% and by 6% in the 25% scenario.

5.2.2 The range of impacts shown in Figure 5 is consistent with CREDS findings that if people who used to commute by car and who are now working from home were to continue to do so for two days per week, almost 14% of work trips would be removed (Marsden, 2021) (the comparable reduction from our model is ~10%.

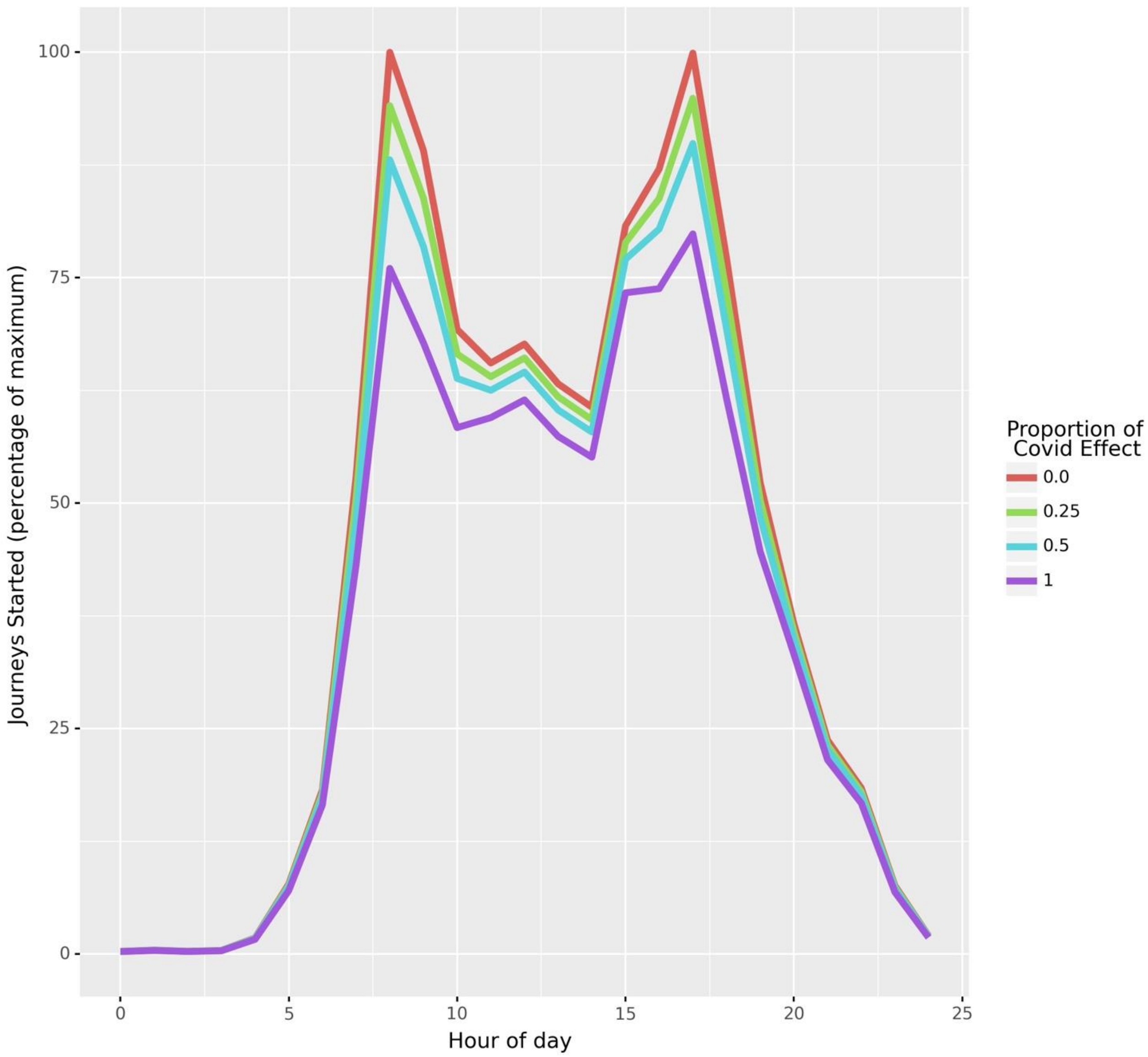



*Figure 5: Changes in travel demand per hour within the EEH area as a result of increased WFH*

## 5.3 Spatial Impacts

5.3.1 The impacts of each scenario can also be applied geo-spatially. Bellow we present the outcomes of the most conservative 25% scenario. Figure 6 and Figure 7 show the percentage reduction in peak hourly demand by Origin and Destination zone respectively within the EEH region under the 25%-COVID scenario (equivalent to continued ~1.25 days home working per week). These figures are based purely on number of journeys per hour and so are not directly influenced by the road network in each MSOA. The variation between areas is down to the variation in the model predictions coupled with existing variation in levels of demand that was present in the baseline matrix.

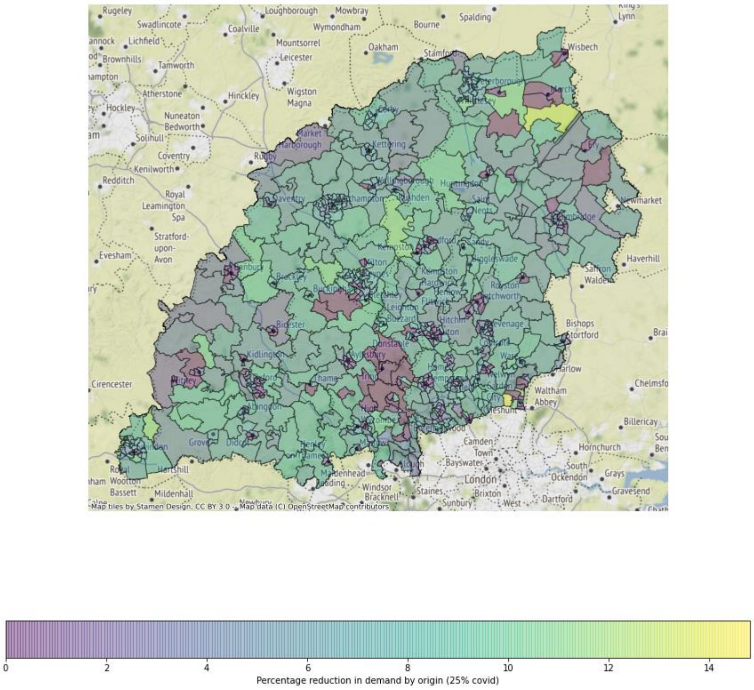



*Figure 6: Percentage Reduction in Demand by Origin (25% COVID Scenario, Method 1)*

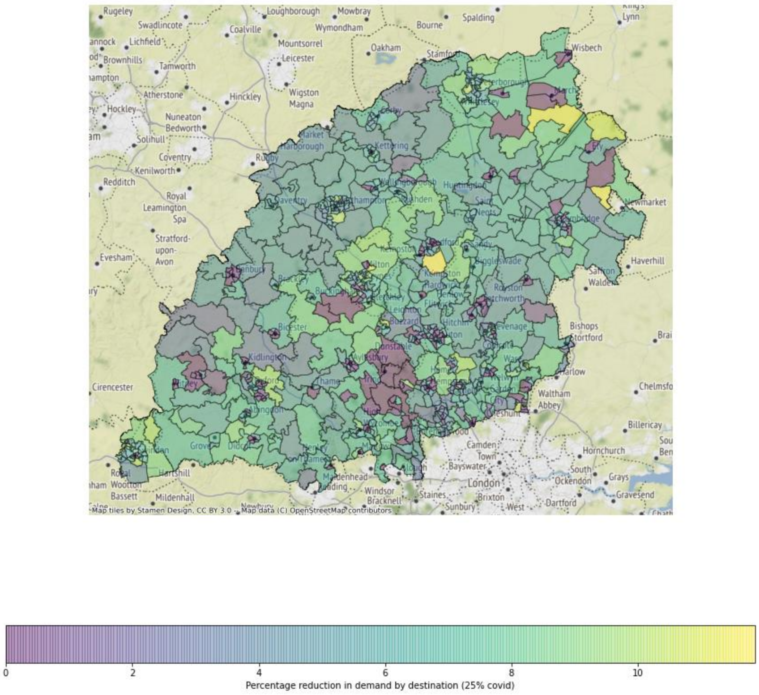



*Figure 7: Percentage Reduction in Demand by Destination (25% COVID Scenario, Method 1)*

5.3.2 In absolute terms this translates into a reduction in demand of between 50-300 vehicles per hour for each zone. The absolute impacts on vehicle flows predicted by the model under the 25%-COVID scenario are set out in Figure 8 and Figure 9 for both Origins and Destinations respectively.

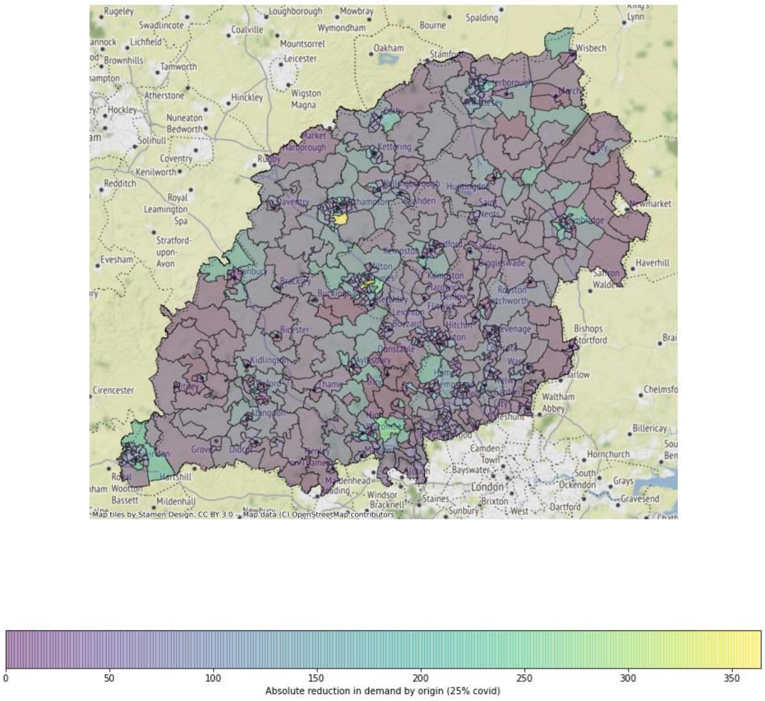



*Figure 8: Absolute Reduction in Demand by Origin (25% COVID Scenario, Method 1)*

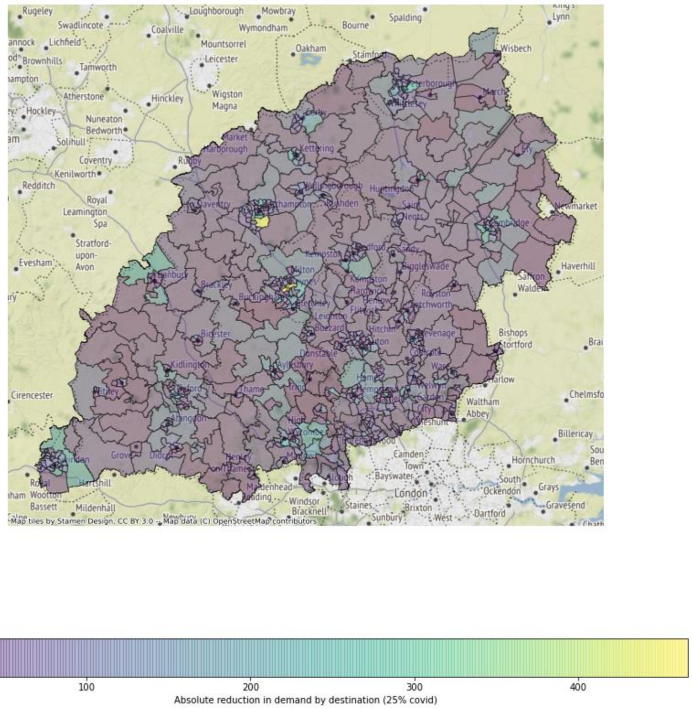



*Figure 9: Absolute Reduction in Demand by Destinatoin (25% COVID Scenario, Method 1)*

5.3.3 Another view on the same data is presented in tabular form below. Table 2 shows the top and bottom 10 MSOAs by absolute peak hourly demand reduction and Table 3 shows all of the LADs within EEH sorted by absolute peak hourly demand reduction. The areas with the largest reductions are Milton Keynes, Swindon, Northampton and Peterborough all with reductions of over 6000 journeys per hour at peak travel times in the 100% scenario. These reductions are between 25% and 30% of the peak demand, clearly illustrating how increases in working from home have the potential to substantially reduce road transport capacity demand in the most congested areas.

| MSOA Code | MSOA Name | Original Peak Hour | Reduction 25% | Reduction 50% | Reduction 100% |
|---|---|---|---|---|---|
| E02005677 | Northampton 028 | 4649 | 364 | 714 | 1432 |
| E02003472 | Milton Keynes 014 | 4579 | 333 | 655 | 1280 |
| E02003669 | Aylesbury Vale 018 | 4133 | 282 | 529 | 1061 |
| E02006823 | Chiltern 013 | 2534 | 251 | 494 | 1043 |
| E02003475 | Milton Keynes 017 | 3240 | 248 | 494 | 1000 |
| E02003761 | Huntingdonshire 009 | 3376 | 238 | 488 | 968 |
| E02005932 | Cherwell 012 | 3656 | 222 | 441 | 868 |
| E02005953 | Oxford 014 | 3982 | 270 | 526 | 858 |
| E02003483 | Milton Keynes 025 | 2193 | 192 | 435 | 839 |

| | | | | | |
|---|---|---|---|---|---|
| E02003725 | Cambridge 007 | 4350 | 192 | 401 | 838 |
| E02004599 | Uttlesford 009 | 45 | 1 | 1 | 4 |
| E02000287 | Enfield 011 | 121 | 3 | 1 | 5 |
| E02000278 | Enfield 002 | 64 | 0 | 2 | 6 |
| E02003393 | Reading 005 | 41 | 6 | 5 | 6 |
| E02003444 | Wokingham 006 | 55 | 1 | 2 | 6 |
| E02003392 | Reading 004 | 62 | 0 | 5 | 7 |
| E02003390 | Reading 002 | 52 | 4 | 3 | 8 |
| E02000279 | Enfield 003 | 71 | 3 | 5 | 10 |
| E02003389 | Reading 001 | 57 | 3 | 1 | 10 |
| E02000277 | Enfield 001 | 59 | 4 | 2 | 11 |

*Table 2: Top and Bottom 10 MSOAs by Hourly Peak Demand Reduction*

| LAD Code | LAD Name | Original Peak Hour | Reduction 25% | Reduction 50% | Reduction 100% |
|---|---|---|---|---|---|
| E06000042 | Milton Keynes | 34818 | 2581 | 5052 | 10145 |
| E06000030 | Swindon | 31596 | 2393 | 4900 | 9740 |
| E07000154 | Northampton | 37153 | 2414 | 4709 | 9196 |
| E06000031 | Peterborough | 22050 | 1581 | 3094 | 6144 |
| E06000056 | Central Bedfordshire | 21171 | 1469 | 2952 | 5904 |
| E07000007 | Wycombe | 21405 | 1452 | 2985 | 5832 |
| E07000011 | Huntingdonshire | 19335 | 1311 | 2643 | 5236 |
| E07000004 | Aylesbury Vale | 19504 | 1270 | 2586 | 5104 |
| E07000012 | South Cambridgeshire | 19423 | 1118 | 2366 | 4648 |
| E06000055 | Bedford | 16741 | 1101 | 2186 | 4256 |
| E07000100 | St Albans | 15010 | 971 | 2040 | 3931 |
| E07000096 | Dacorum | 15500 | 960 | 1912 | 3882 |
| E07000153 | Kettering | 14862 | 929 | 2012 | 3856 |
| E06000032 | Luton | 16385 | 877 | 1811 | 3633 |
| E07000008 | Cambridge | 18845 | 867 | 1740 | 3617 |
| E07000104 | Welwyn Hatfield | 14426 | 887 | 1686 | 3316 |

| | | | | | |
|---|---|---|---|---|---|
| E07000177 | Cherwell | 17130 | 801 | 1674 | 3253 |
| E07000155 | South Northamptonshire | 11405 | 892 | 1641 | 3231 |
| E07000178 | Oxford | 14537 | 828 | 1634 | 3049 |
| E07000005 | Chiltern | 9345 | 728 | 1462 | 3008 |
| E07000180 | Vale of White Horse | 11995 | 748 | 1494 | 2988 |
| E07000097 | East Hertfordshire | 9756 | 656 | 1265 | 2633 |
| E07000179 | South Oxfordshire | 10654 | 691 | 1361 | 2596 |
| E07000156 | Wellingborough | 10365 | 634 | 1278 | 2516 |
| E07000152 | East Northamptonshire | 10505 | 569 | 1240 | 2490 |
| E07000099 | North Hertfordshire | 11924 | 621 | 1222 | 2373 |
| E07000150 | Corby | 7743 | 580 | 1173 | 2277 |
| E07000151 | Daventry | 11001 | 583 | 1138 | 2186 |
| E07000102 | Three Rivers | 8572 | 504 | 1103 | 2057 |
| E07000103 | Watford | 14052 | 539 | 1123 | 2022 |
| E07000010 | Fenland | 5467 | 489 | 1011 | 1968 |
| E07000101 | Stevenage | 9190 | 447 | 1017 | 1890 |
| E07000098 | Hertsmere | 6289 | 395 | 773 | 1587 |
| E07000220 | Rugby | 5583 | 421 | 810 | 1422 |
| E09000017 | Hillingdon | 4829 | 313 | 620 | 1225 |
| E07000006 | South Bucks | 6889 | 308 | 619 | 1202 |
| E07000181 | West Oxfordshire | 8447 | 328 | 641 | 1170 |
| E07000131 | Harborough | 6546 | 275 | 531 | 1108 |
| E07000009 | East Cambridgeshire | 4856 | 214 | 466 | 947 |
| E07000221 | Stratford-on-Avon | 4792 | 228 | 500 | 838 |
| E07000141 | South Kesteven | 4340 | 210 | 430 | 808 |
| E07000095 | Broxbourne | 1969 | 198 | 394 | 788 |
| E06000039 | Slough | 2531 | 171 | 312 | 595 |
| E07000140 | South Holland | 2378 | 138 | 307 | 497 |
| E07000079 | Cotswold | 2924 | 126 | 239 | 476 |

| | | | | | |
|---|---|---|---|---|---|
| E06000054 | Wiltshire | 1413 | 98 | 191 | 362 |
| E07000201 | Forest Heath | 1090 | 95 | 175 | 348 |
| E06000017 | Rutland | 1747 | 67 | 165 | 340 |
| E07000204 | St Edmundsbury | 713 | 74 | 152 | 317 |
| E06000040 | Windsor and Maidenhead | 1358 | 72 | 175 | 299 |
| E07000073 | Harlow | 377 | 39 | 64 | 154 |
| E07000077 | Uttlesford | 649 | 36 | 59 | 141 |
| E07000146 | King's Lynn and West Norfolk | 582 | 36 | 71 | 129 |
| E06000037 | West Berkshire | 715 | 35 | 67 | 113 |
| E06000041 | Wokingham | 519 | 20 | 39 | 98 |
| E07000072 | Epping Forest | 689 | 29 | 53 | 96 |
| E09000015 | Harrow | 401 | 21 | 44 | 90 |
| E09000003 | Barnet | 549 | 21 | 36 | 85 |
| E09000010 | Enfield | 487 | 18 | 25 | 64 |
| E06000038 | Reading | 398 | 15 | 21 | 44 |
| E07000067 | Braintree | 11 | 0 | 0 | 2 |

*Table 3: Hourly Peak Demand Reduction by LAD Sorted by Absolute Reduction*

## 5.4 Corridor Impacts

5.4.1 As discussed in section 3.5.3, for illustrative purposes, the outputs of the demand impacts have been assigned to an EEH network to examine the potential changes on road capacity. As discussed in this section, it is recommended that the model is applied to a calibrated base-year model (e.g. Northamptonshire's county model or the Highways England RTMs) before effects on individual roads can be confidently ascribed. However, these visualisations offer a convenient mechanism to map demand changes to potential impacts on the corridors of interest to EEH. In Figure 10 and Figure 11 we present the potential percentage change in observed traffic flows for the morning peak, highlighting both the Oxford-Milton Keynes corridor and the corridor covering Oxford-Northampton-Peterborough.

5.4.2 It can be observed that under the model during the morning peak, most roads observe traffic reductions in the region of 3%-10%. Approximately 0.5% of links see an increase in traffic however, the majority of these percentage increases represent small absolute changes on low-traffic roads.

5.4.3 **Oxford to Milton Keynes**

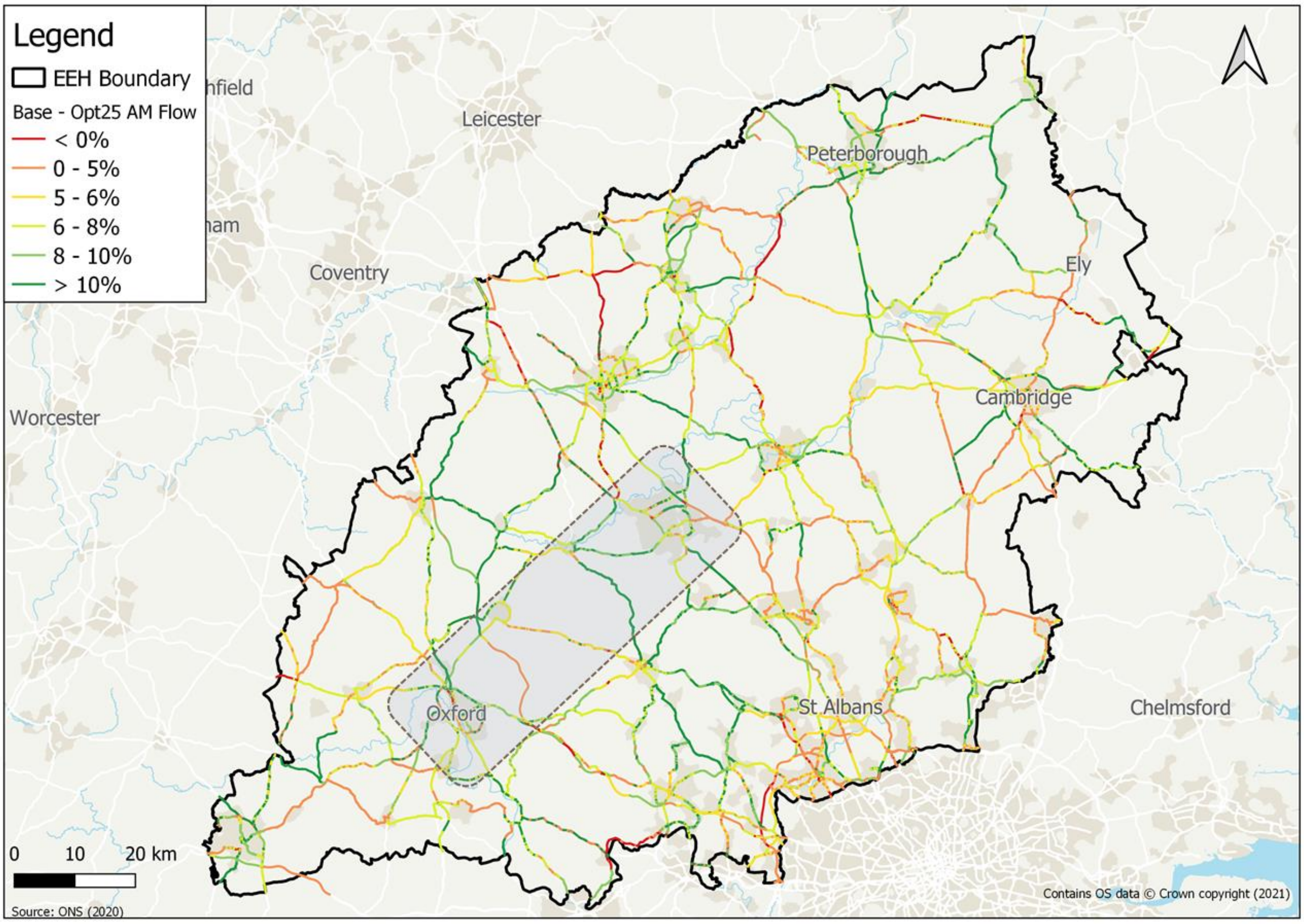



*Figure 10: Potential Percentage Change in Observed Traffic (25% COVID Scenario, Method 1)*

### 5.4.4 Oxford-Northampton-Peterborough

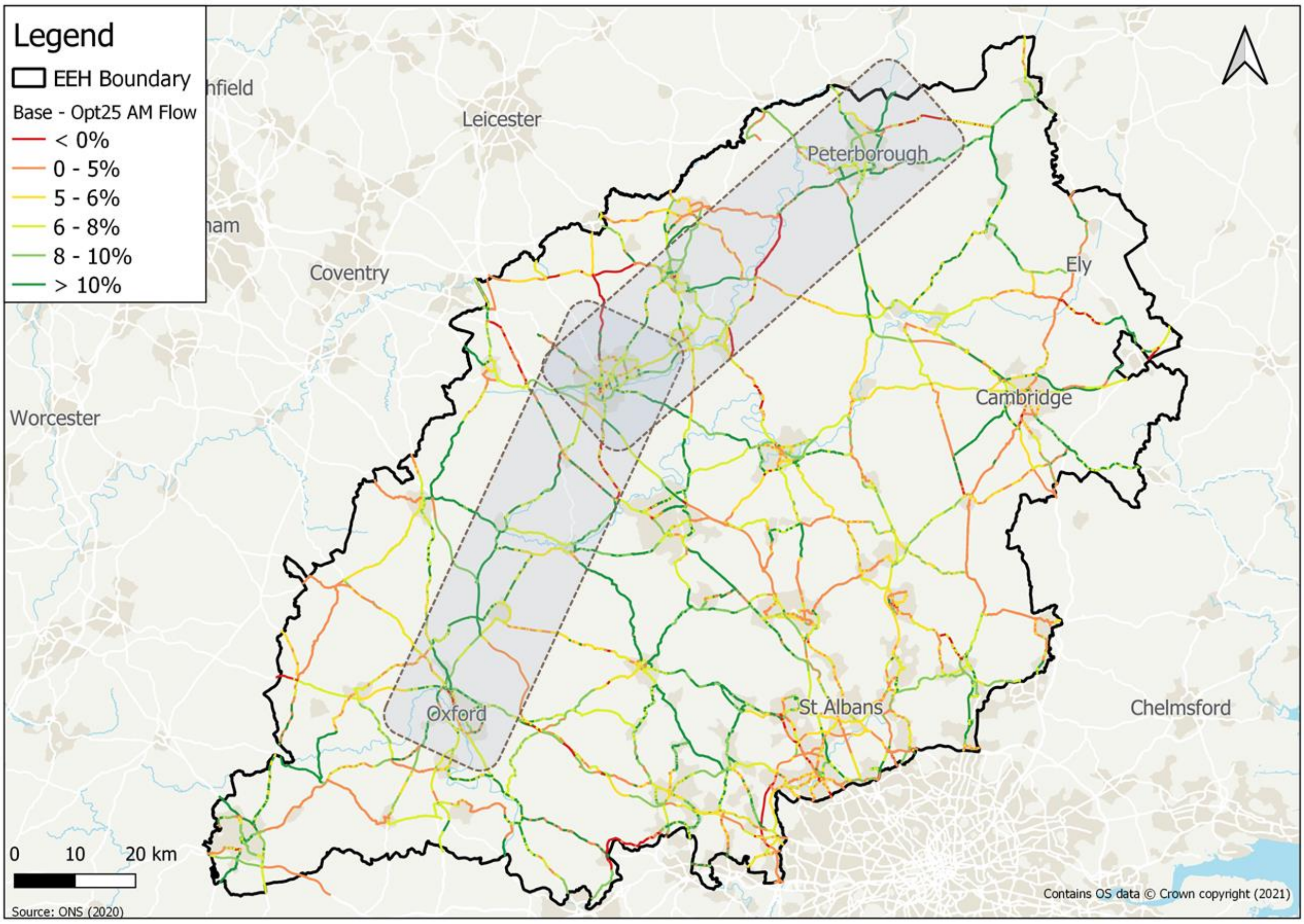



*Figure 11: Potential Percentage Change in AM Observed Traffic (25% COVID Scenario, Method 1)*

5.4.5 The illustration identifies the potential for reductions in peak hour flows within these important connectivity corridors, with some links offering the potential to see reductions in flow of 10% or more.

5.4.6 To further investigate the potential for changes at this scale, we applied the 25% scenario demand model to a calibrated base-year transport model within the Peterborough area – the results are shown in 12. As can be seen the vast majority of links (~90%) see a reduction in flow and those links that see an increased flow are those that had low flow rates in the baseline model (above). However the overall reduction in flow is smaller than that predicted on the basis of the Immense baseline matrix / City Science network with an overall AM reduction in flow of around 3%, at the low end of the 3%-10% range observed across the wider EEH.

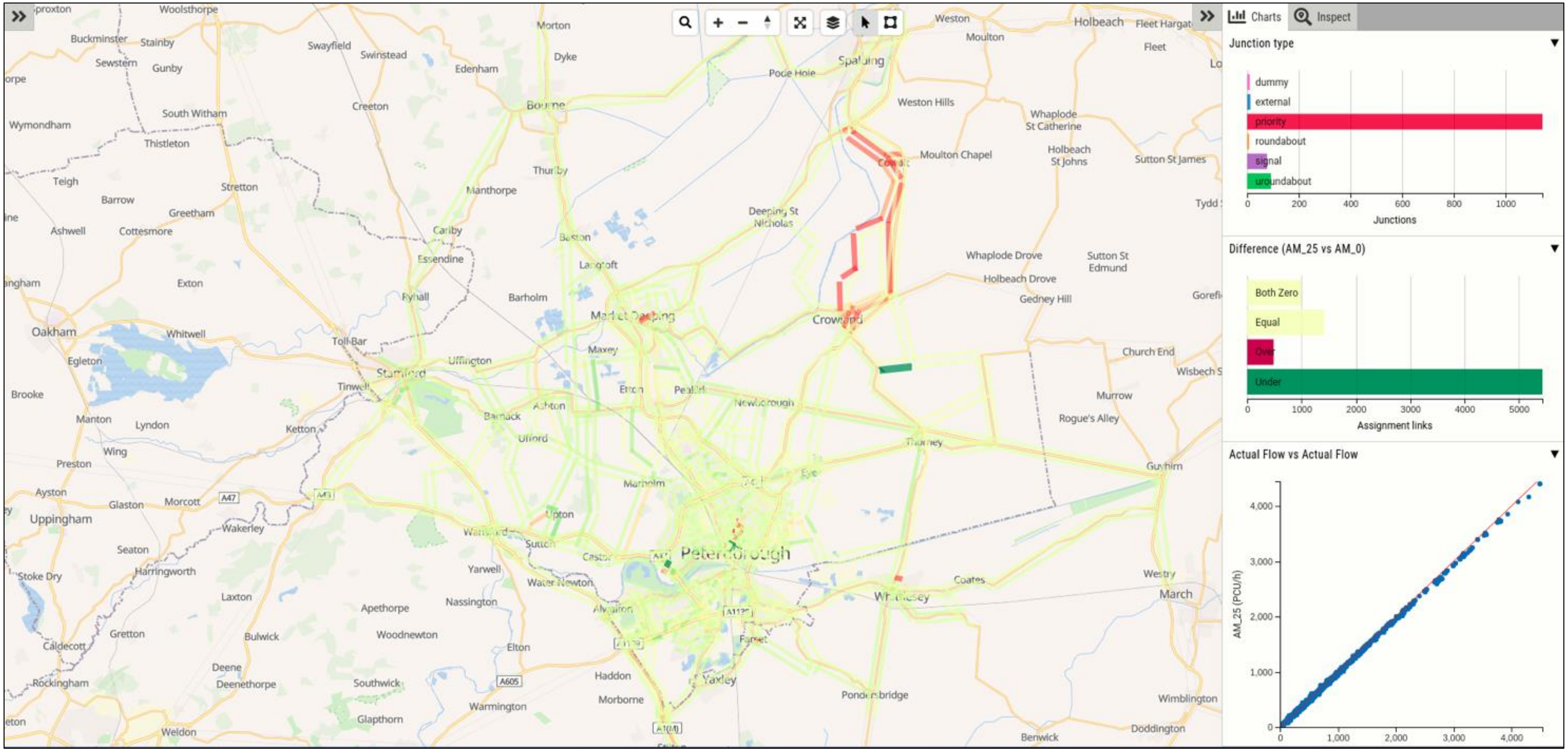



*Figure 12: Potential Change in AM Observed Traffic Based on Calibrated Peterborough Model (25% COVID Scenario, Method 1)*

5.4.7 This highlights the fact that it should not be assumed that changes in demand will map directly to observed changes in flows (i.e. Peterborough's demand reduces by 7% vs. 3% impact on flows). Link specific flows may differ based on both the network and demand used within the underlying models. Possible explainations for the difference between demand reduction and flows observed in the Peterborough case include the following:

- It may be that Peterborough has an unusally high level of long distance non-commuting traffic which masks the reduction in commuting.
- There may be other specific geographic flows which could be uncovered by more detailed analysis.
- Commuter journeys within the Peterbourough area may be unusually short so that reducing the number of commutes has a smaller effect on the overall traffic volumes.
- It may be that commuter journeys passing through the Peterbourough area are accounted for differently within the two demand matrices we have investigated.

5.4.8 To fully understand the origin of the differences between the predictions based on the two matrices would likely require evaluation of changes to distance weighted flows and a more in-depth geographic analysis of Peterborough specific flows / changes as well as flows of long distance traffic using the transport corridors.

# 6 Effect of Digital Connectivity

6.1.1 One suprising aspect of the modelling work was that broadband speed did not emerge as a significant predictor of propensity to work from home. This lack of relationship between digital connectivity and propensity to work from home needs to be treated with some caution, however, for two reasons: 1) In our previous work we observed that the overwhelming limiting factor for working from home was related to the employer rather than the employee. Indeed, in models based on the 2011 census by far the most significant predictor of working from home was self-employment, suggesting that prior to covid most employers were not prepared to allow large scale working from home. 2) Farming-related professions are one of those most likely to identify as working from home, but they are also concentrated in rural areas with poor digital connectivity. It seems likely that this may mask the negative effect of poor broadband connectivity in those areas.

6.1.2 Possibly the most sensible conclusion to draw from this is that the current digital infrastructure is not a major bottleneck for working from home. However, it may be that over time disparities between different locations in terms of digital connectivity would drive changes in land use demand and so it makes sense to aim policy towards lifting the digital connectivity to the level of the best connected areas.

# 7 Conclusions & Next Steps

7.1.1 This project has developed a model that can be used to explore different future scenarios of Working-from-Home. The model applies the effects geospatially based on detailed geodemographic data. The effects can then be routed through a network to translate these demand effects into potential traffic and capacity release impacts along key corridors or routes.

7.1.2 Our model predicts that if people who used to commute by car and who are now working from home were to continue to do so for two days per week, between 10% to 12% of peak hour traffic would be removed. This is consistent with independent findings from the University of Leeds who estimate that this level of home working would reduce morning car trips by 14%.

7.1.3 This level of working from home has the potential to have significant impacts on the road network. To analyse this we apply a 25%-COVID scenario (roughly equivalent to ~1.25 days working from home) to the baseline demand provided. While this scenario results in only a 6% reduction in total peak hour travel, the model predicts that most roads would experience traffic reductions in the region of 5%-10%. Localised impacts are expected to differ due to the precise make-up of resident demographics and sector-mix in the economy and the speed-flow characteristics of specific roads.

7.1.4 When applied to a calibrated demand matrix for a subset of the EEH network based around Peterbourough the model predicted a similar pattern of flow reductions although the absolute level of these was slightly lower. Further investigation would be required to explore the reasons underlying these differences.

7.1.5 **Next Steps:** The modelled outputs will be made available for the purposes of further analysis within the corridor studies. This will include two forms of demand matrices – both in agent-based form for integration with the EEH Policy tool, and in traditional form for analysis of travel desire lines along the key corridors.

7.1.6 From a policy perspective these results suggest that there is currently a major opportunity to lock in, and maybe even improve on, the reductions in travel demand resulting from the pandemic. We suggest that there are three key areas that policy makers should focus on:

1. Incentivising employers to continue to allow and encourage home working – if employees across the region could be encouraged to work at home two or three days a week then there is potential for even greater capacity release.
2. Encouraging a return to public transport use – one negative effect of Covid has been the switch from public transport to car use. Policy should be aimed at reducing this and also at preventing further switching. In particular, transport season tickets aimed at users commuting two or three days a week should be encouraged, to ensure that public transport users switching to a hybrid homeworking model are not insentivised towards car use.
3. Leveling up digital infrastructure to match the best available speeds in the region.

# 8 Appendix: Further Scenarios Run on Peterborough Model

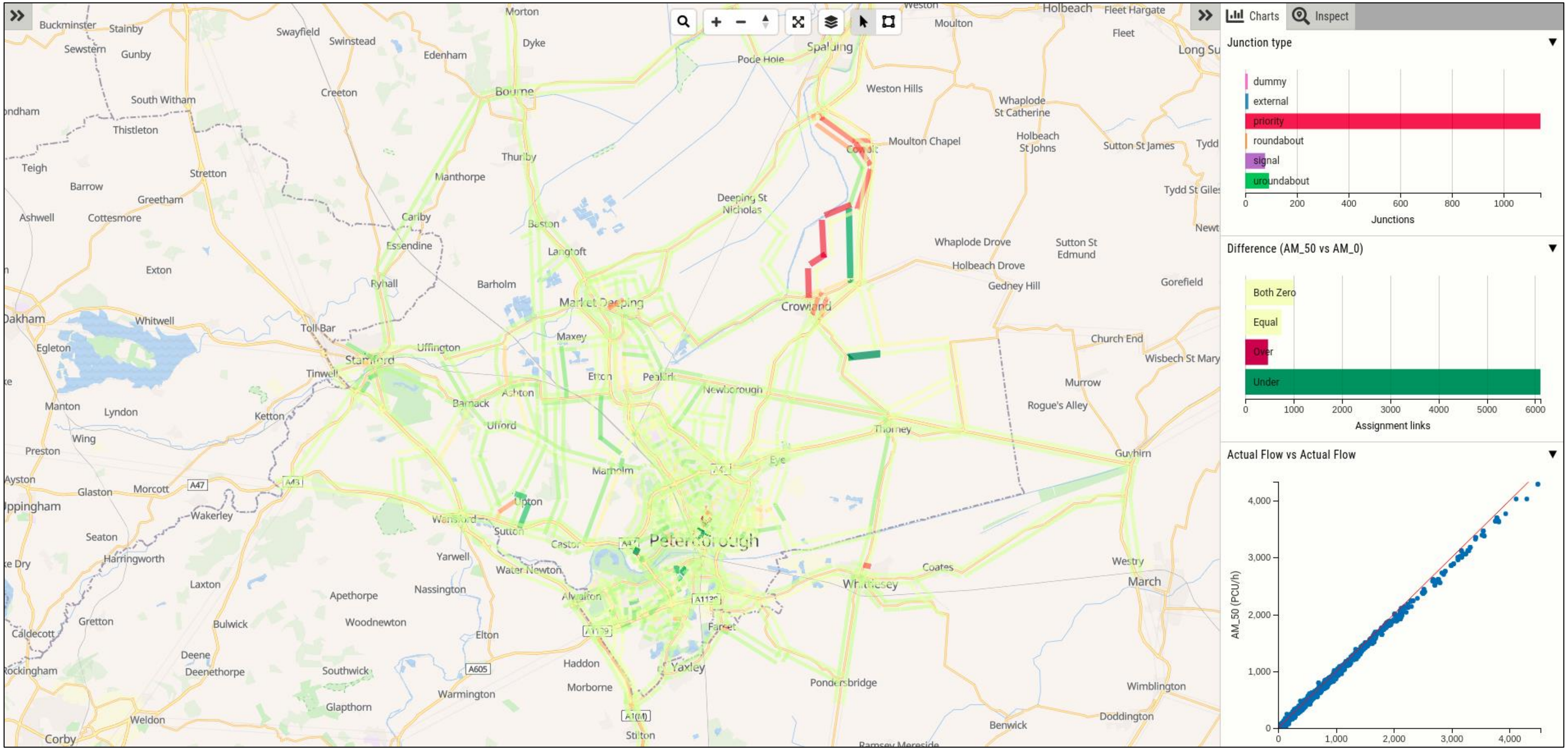



*Figure 13: Potential Change in AM Observed Traffic based on Calibrated Peterborough Model (50% Scenario, Method 1)*

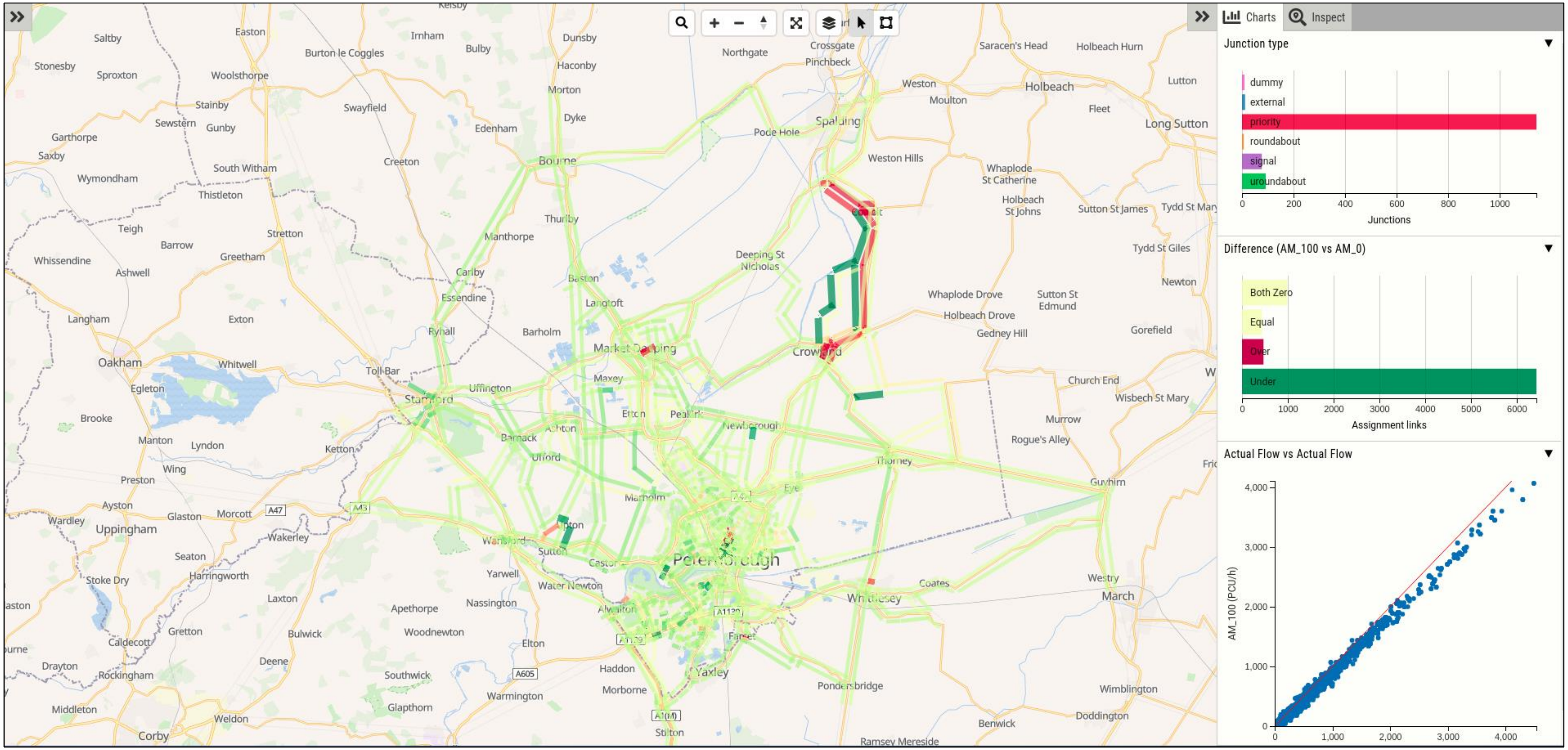
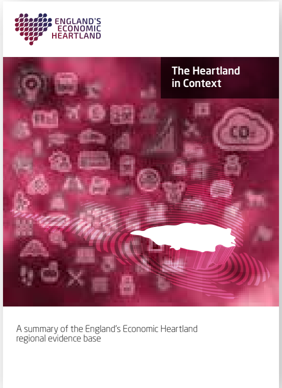
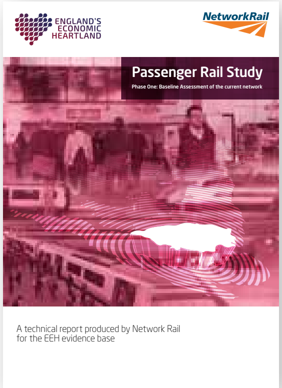


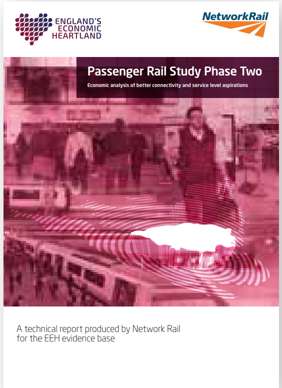

*Figure 14: Potential Changes in AM Observed Traffic Based on Calibrated Peterborough Model (100% COVID Scenario, Method 1)*

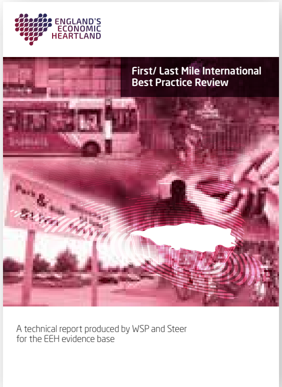
Englands Economic Heartland has released a number of technical studies and documents which underpin the Transport Strategy.
These are available on our website www.englandseconomicheartland.com

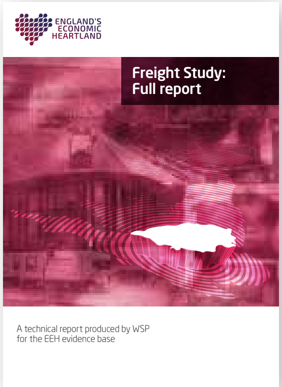







## Get in touch

England's Economic Heartland Strategic Alliance
EEH Business Unit
c/o Buckinghamshire Council
Walton Street
Aylesbury
HP20 1UA

For general enquiries please contact 01296 382703
or email englandseconomicheartland@buckscc.gov.uk

www.englandseconomicheartland.com

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