EVALUATING THE IMPACT OF A WORKPLACE PARKING LEVY ON LOCAL TRAFFIC CONGESTION: THE CASE OF NOTTINGHAM UK

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ABSTRACT

A Workplace Parking Levy (WPL) scheme raises a levy on private non-domestic off street parking provided by employers. In April 2012 Nottingham became the first UK City to implement such a scheme with the revenue generated hypothecated for funding transport improvements.

The lag between the introduction of the WPL and the opening of related public transport improvements represents an opportunity to study the impact of a WPL on congestion as a standalone measure. In order to achieve this it is necessary to consider changes to variables external to the WPL, which also impact on congestion, which may obscure any beneficial impact of the scheme. An autoregressive time series model which accounts for the impact of these exogenous variables is used to evaluate the impact of the introduction of the WPL on congestion. Delay per Vehicle Mile is used as the dependent variable to represent congestion while the number of Liable Workplace Parking Places (LWPP) is used as a continuous intervention variable representing the introduction of the WPL. The model also contains a number of economic, transportation and climatic control variables.

The results indicate that the introduction of the WPL as measured by the number of LWPP has a statistically significant impact on traffic congestion in Nottingham. Additionally, external explanatory variables are also shown to impact on congestion, suggesting that these may be masking the true impact of the scheme. This research represents the first statistical analysis of the link between the introduction of a WPL and a reduction in congestion.
1 INTRODUCTION

In April 2012 Nottingham City Council introduced a Workplace Parking Levy (WPL) which levied a charge on occupied private non-domestic off-street parking places. These are termed Workplace Parking Places (WPPs) and are defined as places occupied by vehicles used by employees, regular business visitors or students. It is the first charge of its type in the UK and indeed, in Europe.

The WPL has a dual role; firstly to act as a transport demand management measure and secondly to raise hypothecated funds for transport improvements. The money raised by the WPL is funding two new tram lines, improvements to Nottingham Railway Station and quality enhancements to the LinkBus services. The WPL scheme and the above mentioned public transport improvements comprise the overall “WPL package” and are intended to complement each other to enhance the transport demand management effect. For the 2016/17 financial year the charge per WPP is £379.

The aim of this paper is to report, for the first time, on a statistical evaluation of the impact of the introduction of the WPL on levels of peak period congestion in Nottingham. Hamer et al. (1) noted that such schemes are seldom introduced in isolation which makes it difficult to isolate the impact of the charging scheme from that of other transport improvements or traffic restraint measures. However, the research detailed in this paper takes advantage of the opportunity to study the stand alone impact of the WPL by examining the time period from 2010, when employers started to take pre-emptive action to reduce their liability for the provision of WPPs, up to 2015 when the principal public transport intervention of the WPL package, NET Phase 2, was completed.

The paper explores the relationship between City wide levels of congestion, the introduction of the WPL and important explanatory variables, including the key contextual factors that may obscure any impact of the introduction of the WPL. In order to achieve the above aim this research utilises a statistical approach to compare relevant time series data which provides an assessment of the relative impact on congestion of these variables.

The paper is structured as follows. A literature review is followed by the methodology section which details the application of a statistical approach to assess the impact of the supply of workplace parking on traffic delay. The results of this research are then presented and discussed. Finally, the conclusions are presented, including limitations and a suggested direction for further research.

2 LITERATURE REVIEW

In order to meet the above research aim it is necessary to understand how to define and measure congestion, what factors drive congestion, the impact that existing parking space levies have had on congestion and finally what statistical approaches have been used successfully for achieving similar research aims.
Defining traffic congestion

The UK Commission for Integrated Transport recommended that a measure of congestion be based on the difference between free flow speed and actual speed (2). This indicator was more fully defined in the follow up report “A measure of road traffic congestion in England” (3). This concept has become known as delay. Taylor et al. (4) identified a number of measures and definitions for congestion including the congestion index which compares total travel time on a link as a proportion of expected free flow travel time. This can be averaged for all vehicles on a link per time period and can be applied on a segment or corridor level by aggregating the travel times for multiple segments. This approach is useful when comparing levels of congestion across different geographic locations (5). However, neither average delay nor the Congestion Index takes into account traffic flow.

The UK Department for Transport (DfT) outlined a methodology to calculate journey time per vehicle mile to monitor congestion on locally managed A roads (6). This normalises journey time by link length and flow. US Department of Transportation Guidance for measuring effectiveness for highway schemes defines a similar measure which calculates delay per vehicle mile travelled (7) and combines the advantage of a spatially comparable metric and a real world unit of measurement. Delay per Vehicle Mile (DVM), therefore, combines the advantages of both the Congestion Index and Journey Time per Vehicle Mile and thus this is the measure of congestion used in this research.

Drivers of congestion

In Nottingham, the reality has been that, since 2010, congestion levels have increased and similar increases are observed in other UK Core Cities (8). Despite a fall in the supply of WPP and other positive changes in employer behaviour, it has not been possible to observe any impact the introduction of the WPL has had on congestion in Nottingham. It is therefore important to identify the key factors or ‘drivers’ which are likely to impact on traffic congestion and may obscure any beneficial impact arising from the introduction of the WPL. These contextual factors can then be taken into account within any potential research methodology. Tanner (9) presented research that examined factors that contributed to congestion; he demonstrated the importance of income levels, fuel price and economic output in determining the demand for travel.

More recently, and specific to the UK context, Transport for London carried out a detailed review of factors which contribute to traffic speeds in London (10). Their work presents a reasoned narrative that points to the importance of household income levels and the effect of reductions in network capacity as road space is re-allocated to public transport and cycling. It also notes that not only overall population change is significant, but that the nature of this change needs to be considered, for example changes in the demographics of the working age population may result in changes to levels of car ownership and propensity for car use.

The DfT identified three key drivers for the demand for travel in a report detailing their road traffic forecasting (11): (i) population growth, (ii) GDP per capita/disposable income and (iii) the cost of motoring.

DfT (11) also points out the importance of the availability of alternatives to using the car as well as the cost of those alternatives.
There are also factors which impact directly on congestion by impeding the speed of traffic or by reducing capacity (12). The DfT identifies weather conditions as being an important factor, for example, wintry weather slows traffic and can influence mode choice, while increased rainfall is postulated as a causal factor for an increase in journey times in recent years. Jia et al. (13) examined the impact of rainfall of various intensities on traffic speeds in differing urban situations in Beijing and concluded that the closer to capacity the link and the lower the intensity the rainfall, the less impact on speed. However, they still demonstrated that precipitation levels were a significant factor in reducing speeds in an urban setting.

### The impact of Workplace Parking Levies on congestion

Although Hamer et al. (1) and Richardson (14) report on the impact on headline indicators related to the impact of the similar schemes in Sydney and Perth in Australia, there is little empirical research which specifically seeks to attribute an impact on congestion to the introduction of a WPL as a standalone measure. Hamer et al. (1) concluded that the impact on congestion of the Sydney scheme was minimal while Richardson (14) reports that the Perth Parking Space Levy (PSL) was associated with a significant mode shift away from the car and associated reduction in traffic levels on major radials Richardson presents figures from the Australian Bureau of Statistics for Perth which show that prior to implementation of the PSL only 35% of journeys to work were on public transport; however by 2010 this had risen to over 50%, while car modal share had fallen by a similar amount clearly demonstrating a modal shift to public transport. Richardson reports that the volume of car traffic on radials providing access to the city reduced by between 3% and 20% in the three years following implementation of the scheme and that traffic within the city has continued to decline.

### Statistical Methodologies

A range of statistical methodologies have been employed to evaluate the relative impact of differing causal factors on travel demand. For instance, Hahn et al. (15) used a least-squares regression model to investigate the relationship between congestion, travel demand and road capacity in US cities. They determined that freeway lane miles, population density, net land area and bus revenue miles could explain about 61% of the changes observed in congestion levels. A linear regression model may however fail to control for serial autocorrelation inherent to a time series observations. Quddus et al. (16) utilised an alternative time series analyses to study the impact of the introduction of the London Congestion Charge (LCC) on retail sales in London. They employed the Prais-Winsten regression model, a log-linear model with AR(1) disturbance, to explore the impact of a number of potential explanatory variables including a dummy intervention variable representing the introduction of the LCC. Li et al. (17) utilised difference in difference (DiD) estimation to analyse the effects of the introduction of the LCC on road traffic casualties. DiD estimation requires a control group (unlike the other techniques mentioned in this review) and for their study accident rates in Birmingham, Leeds and Manchester were used. This approach can therefore allow for national and local trends as well as seasonality. Cole et al. (18) employed an Autoregressive Integrated Moving Average (ARIMA) model to investigate the impact on the yields of recyclable and non-recyclable waste of changes to collection schedules and policy. This model was able to quantify the success of the interventions analysed and to predict the impact of seasons and the number of working days on quantities of waste recycled.
It is concluded from the above literature review that a delay based metric normalised by both flow and road length would be the most appropriate measure of congestion as it allows for temporal and spatial comparison and is a ‘real world’ unit. The literature review reveals that economic/demographic factors, weather conditions, the relative cost of travel by each mode and changes to network capacity are key determinants in the changes to levels of congestion and that these need to be accounted for in any research related to congestion changes over time.

An examination of previous research which applies time series modelling techniques to similar research questions shows that ARIMA models and DiD estimation are both options. However, it may be appropriate to use the Prais-Winsten regression model with first-order autoregressive (AR1) disturbance, as this provides easily interpretable and flexible output. This approach requires a dependent variable, an independent intervention variable and relevant independent exogenous variables to be specified. The morphology of these variables and data quality determines both the final form of the model and the quality of the output. Importantly, a Prais-Winston regression is also capable of correcting for autocorrelation which may be present in the data used for the model. Sections 3 and 4 outline this chosen statistical approach in more detail.

3 DATA DESCRIPTION

As discussed in the previous section the chosen statistical approach requires a dependent variable, an independent intervention variable and relevant independent exogenous variables to be specified. The morphology of these variables and data quality determines both the final form of the model and the quality of the output, therefore, a full understanding of these is required.

The available datasets varied in terms of observation frequency from annual to daily data and thus scale effects need to be considered. It was decided that using weekly data provided a sensible level of aggregation as it provides a sufficient number of data points while avoiding the inherent variability of daily data. There could also be data sparsity issues with some of the data sets if daily data was used. There are thus 260 weekly values in each time series. If the data was aggregated to a monthly level this would reduce the number of observations to just 60 and this is considered sub optimal for the statistical approach adopted, especially if explanatory variables are included. However in order to obtain weekly data points from data which was collected less frequently it was necessary to interpolate weekly values for a number of the variables, including the continuous intervention variable LWPP. This is discussed in more detail below with respect to the intervention variable and in Table 1 for the other independent variables.

The Dependent Variable - The dependent variable quantifying congestion, Delay per Vehicle Mile (DVM) is collated across all major radial routes inbound into Nottingham and in both directions on the main orbital route the A6514 (the Nottingham Ring Road) in the AM Peak period (07:00-10:00) for cars and LGVs. The total length of the network used in this study is 68.2 miles. This metric is calculated using average journey time generated from the Trafficmaster satellite navigation system fitted to many fleet and private vehicles in the UK. This data source is also used by the DfT to generate national journey time statistics in
preference to other similar data sources. The mean DVM value across the study period is 1.22
minutes.

**Continuous Intervention Variable - introduction of the Nottingham WPL** – The
mechanism by which the introduction of the WPL is likely to impact the demand for travel is
by a reduction in both the supply and demand for parking at work. It is assumed that the
reduction in both is, for the period between 2009 and 2013, a direct result of introducing the
WPL.

This can be quantified by the number of Workplace Parking Places (WPP) provided across
the Nottingham City area. Unfortunately, the time series pertaining to total WPP, which
includes exempt employers, is not complete and therefore could not be used, thus the quantity
of Liable WPP (LWPP) is used as a continuous intervention variable. LWPP refers to WPPs
which are liable to the full WPL charge (i.e. are not exempt or subject to a 100% discount).

There are two main sources of data which contribute to this time series:

1. The April 2010 Off-Street Parking Audit (OSPA) – this was a pre WPL survey of
   LWPP in Nottingham.
2. The number of LWPP licenced under the requirements of the WPL scheme.

As the supply of off-street parking is known to exceed demand, LWPP up to April 2010 is
calculated based on the number of jobs located in the City using April 2010 as a reference.
Between the OSPA survey in April 2010 and the commencement of licencing in September
2011 it is assumed that the number of LWPP started to decline in response to the WPL 1 year
prior to the introduction of licencing, but that the rate of decline increased the closer to the
date of implementation. This assumption is supported by the chronology of actions taken by
major employers to reduce their WPL liability as well as the programme of engagement
undertaken by Nottingham City Council with employers to explain their responsibilities
under the WPL scheme and to provide support in terms of limiting their liability. Therefore,
the weekly values between the OSPA 2010 data point and first availability of licencing data
in September 2011 have been estimated by using a non-linear interpolation which reflects this
evidence. Finally, the seasonality observed in 2013 and 2014 was superimposed on the
interpolated data prior to April 2012. The normal method of applying seasonal indices based
on a moving average was used to achieve this.

Figure 1 shows the time series for the dependent and independent intervention variables. It is
the nature of the relationship between these two time series and the introduction of the WPL
which is the focus of this research.
Exogenous Independent Variables

These variables represent factors which, based on the literature review, are likely to impact on the dependent variable, DVM, but are external to the WPL intervention. They are:

- Monthly total rainfall
- Average minimum monthly temperature
- Working Age Population minus Total Benefit Claimants
- Index of road work activity
- Fuel price
- Season
- Public transport patronage
- Liable Workplace Parking Places (introduction of the WPL)

These variables are listed and specified in Table 1.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Weekly average (2009-2013)</th>
<th>Frequency</th>
<th>Level of geographic aggregation</th>
<th>Time Period</th>
<th>Method used to synthesise weekly time series</th>
<th>Source</th>
<th>Notes and Justification for inclusion in model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>mm</td>
<td>11.17</td>
<td>Monthly</td>
<td>Area</td>
<td>NA</td>
<td>Met Office Station at Sutton Bonnington</td>
<td></td>
<td>This is monthly precipitation in mm converted to weekly values. As discussed earlier, literature shows rainfall is linked to reduced traffic speeds. In order to allow for the differing number of weeks in each month the following method was used to divide up the monthly rainfall: RainMnth/((365-28)/11)/7 , Except Feb which is calculated by: (RainFeb/4)</td>
</tr>
<tr>
<td>Average minimum temperature</td>
<td>deg C</td>
<td>6.12</td>
<td>Monthly</td>
<td>Area</td>
<td>NA</td>
<td>Met Office Station at Sutton Bonnington</td>
<td></td>
<td>This is an important as a proxy for wintry weather such as snow and ice which both slows traffic speed and reduces traffic flow.</td>
</tr>
<tr>
<td>Working age population minus Total Out of Work Benefit Claimants</td>
<td>persons</td>
<td>370337.46</td>
<td>Annual/Quarterly</td>
<td>Greater Nottm</td>
<td>NA</td>
<td>Linear Interpolation</td>
<td>Office for National Statistics (ONS)</td>
<td>The working age population of Greater Nottingham rose steadily throughout the study period and this increase will potentially offset the impact of fluctuations in the number of out of work benefit claimants. It would therefore seem sensible to consider the total working age population that is not claiming out of work benefits. Note that data for Greater Nottingham is used for this metric.</td>
</tr>
<tr>
<td>Index of roadwork activity</td>
<td>numeric</td>
<td>1.34</td>
<td>Weekly</td>
<td>Greater Nottm</td>
<td>NA</td>
<td>NA</td>
<td>Nottingham City Council 2015</td>
<td>A road works index was compiled to quantify disruption to traffic caused by the construction phase of the following major transport improvements: • NET Phase 2; the construction of two new tram lines. • A453 Dualling • Major improvement scheme for the A6514 Nottingham Ring Road These were further subdivided by location and each element was rated out of three in terms of disruption to the network. The score for each week was then summed to create a weekly score.</td>
</tr>
<tr>
<td>Fuel Price</td>
<td>pence per litre of unleaded</td>
<td>124.26</td>
<td>Monthly</td>
<td>UK</td>
<td>NA</td>
<td>Linear Interpolation</td>
<td><a href="http://www.petrolprices.co">http://www.petrolprices.co</a> m/the-price-of-fuel.html</td>
<td>It was decided that petrol prices were the most relevant cost of motoring as this is not a fixed cost and subject to short term market variations.</td>
</tr>
<tr>
<td>Season</td>
<td>Dummy Variable</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>This is a dummy variable</td>
<td></td>
</tr>
<tr>
<td>Public Transport Patronage</td>
<td>Journeys (millions)</td>
<td>1.44</td>
<td>Quarterly</td>
<td>Greater Nottingham</td>
<td>00:00 - 23:59</td>
<td>Quarterly figure divided by 13 and applied to each week in the quarter</td>
<td>Nottingham City Council 2015</td>
<td>Total combined quarterly bus and tram patronage in Greater Nottingham. This indicator is used to reflect the supply and relative cost of public transport options. It was not possible to synthesise a time series to reflect the local cost of public transport, due to complex ticketing arrangements.</td>
</tr>
<tr>
<td>Introduction of the Nottingham WPL</td>
<td>Liable Workplace Parking Places</td>
<td>29983.58</td>
<td>April 2010, then Sep 2011 then monthly from 01/04/2012</td>
<td>Nottingham City</td>
<td>NA</td>
<td>Non-linear Interpolation</td>
<td>Nottingham City Council 2015</td>
<td>Number of Workplace Parking Places in Nottingham which are liable for the WPL charge.</td>
</tr>
</tbody>
</table>
Having identified the relevant data sets that are available the next step was to consider the potential relationship between these variables in order to arrive at a testable hypothesis. Public transport patronage, working age population in work, fuel price, the time of year and the introduction of the WPL will all impact on Vehicle Miles Travelled (VMT) by determining the demand for travel by car rather than directly acting on (DVM) i.e. congestion. Indeed, only the weather conditions and roadworks will impact directly on total delay by restricting capacity and/or introducing conditions that will physically slow the traffic. VMT and DVM are thus strongly related and it is likely that any time series model will highlight this were VMT to be used as an explanatory variable for delay (10). This will not meet the research aim as it is important to know the relationship between congestion and those factors that impact on it by causing a change in VMT.

Figure 1 above shows superficially that a fall in the number of LWPP appears to correspond with a fall in DVM between late 2010 and early to mid 2012. However, it is also true that other external explanatory variables do show a trajectory which could also lead to a fall in DVM for example;

- The period 2011 – 2012 was relatively mild and dry.
- An increase in the number those claiming out of work benefit, i.e. a rise in unemployment.

However, the number of jobs located in Nottingham and the working age population continued to grow strongly throughout which would seem to support a steady growth in DVM over the period. Given these contradictory indicators, the following hypothesis will be tested by a suitable statistical model: The fall in LWPP from 2010 and early 2012 has contributed to the observed reduction in DVM from late 2010 to mid 2012.

As discussed in section 2, two statistical models that can be used to achieve the study aim are: Prais-Winsten regression and ARIMA models. A empirical analysis of the autocorrelation and partial autocorrelation functions indicates that an ARIMA model may not be essential if the Prais-Winsten regression model can handle serial autocorrelation in the time series of DVM. Therefore, the Prais-Winsten regression model has been chosen as the most parsimonious statistical model for this study.

**Model Specification**

Initially a simple linear-log model was employed given by

\[ y_t = \alpha + \beta_k X_t + \gamma \ln LWPP_t + \theta_mD_t + \epsilon_t \]  

(1)

where, \( y_t \) is the value of DVM, the dependent variable, for period t (in this case week t), \( X \) is a \( k \) vector of continuous explanatory variables some of which are logged, \( LWPP \) is the continuous intervention variable that is expected to influence \( DVM \), \( D \) is an \( m \times 1 \) vector of categorical/dummy explanatory variables, \( \epsilon \) is white noise. \( \beta, \gamma \) and \( \theta \) are appropriately sized vectors of parameters to be estimated.

If the residuals from the above model are not normally distributed (by the use of Kolmogorov-Smirnov test) and there is a clear evidence of serial autocorrelation (by the use of Durbin-
Watson $d$-test) in the dependent variable then the Prais-Winston regression model should be employed. In this model, the errors are assumed to follow a first-order autoregressive AR(1) disturbance as shown below:

$$
\epsilon_t = \rho \epsilon_{t-1} + \epsilon_t
$$

(2)

Where $\rho (-1 < |\rho| < 1)$ is the autocorrelation coefficient, and $\epsilon_t$ is independent and identically distributed with zero mean and a constant variance $\sigma^2$.

The model presented in equations (1) and (2) can be estimated by using the Prais–Winsten transformed regression estimator that is basically a generalised least-squares estimator (19).

Multi-collinearity is unlikely to be a problem within these variables as they are, for the most part, intuitively unrelated. This would not have been the case if, for example, VMT had been included as an explanatory variable. A dummy variable is used to control for seasonality which is inherent in traffic congestion data.

5 RESULTS

Firstly, a simple linear regression model as shown in Equation (1) was developed using the data described in section 3. Although this yielded an excellent goodness-of-fit statistic (i.e. $R^2$ value of 0.87), the Kolmogorov-Smirnov test indicated that the residuals are not normally distributed and the Durbin-Watson $d$-test identified that there is a problem of serial autocorrelation. Therefore, the coefficients from the linear model may not be appropriate to evaluate the impact of the intervention. Subsequently, the Prais-Winston regression model with AR(1) disturbance was employed. The results are presented in Table 2. The model goodness-of-fit, the adjusted $R^2$, is 0.62 which is very good for this type of model and commensurate with similar work (15). An $F$-value of 42.9 with probability close to 0 shows that, overall, the model applied can statistically significantly predict the dependent variable. The Durban Winsten $d$-statistic of 2.04 demonstrates that the model has successfully compensated for serial correlation by applying the Prais-Winston transformation. The value of the autocorrelation coefficient was found to be 0.33 indicating that the errors are serially correlated and the application of the Prais-Winston regression model is appropriate.

Having established the model is a good fit to the data an examination of the regression coefficients and their statistical significance can now be undertaken.
The fitted model is: (see Table 2):

\[ \text{DVM} = -107.66 + 0.6735 \ln(LWPP) - 0.0038 \text{FuelPrice} - 0.0145 \text{MinTemp} + 7.9138 \ln(WAPmOWB) + 0.0427 \text{RoadWrks} + 0.6117 \text{BusPat} + 0.1484 \text{Autum} + 0.1263 \text{Winter} + \varepsilon_t \]

Where \( \varepsilon_t = 0.3254 \varepsilon_{t-1} + \varepsilon_t \)

Table 2 shows that LWPP has a statistically significant impact on DVM. The t-statistics and p-values for LWPP show that there is less than a 5% chance that the co-efficient predicted
has occurred by chance i.e. the variable is statistically significant at the 95% confidence level.

A further examination of the $p$ values reveals that the model provides more than 99.9% certainty that a positive relationship exists between the intervention variable and the dependent variable, i.e. that a decrease in the quantity of Liable Workplace Parking Places would have resulted in a reduction in congestion if all other variables are kept constant. The elasticity for DVM with respect to LWPP\(^1\) is calculated as 0.55. This indicates that a 1% reduction in LWPP explains a 0.55% decrease in DVM. Further interpretation is provided in the next section.

The following exogenous independent variables are also statistically significant with respect to having an impact on delay:

- Road Works Index - as the number of roadworks increases DVM increases. This is expected considering that roadworks will reduce capacity on a link through lane closures and pinch points such as temporary traffic signals. Indeed when the road work index is plotted against DVM it can be seen that the surge in DVM experienced in late 2013 corresponds with the peak in road work activity in the study period.
- Average Minimum Temperature - as temperature decreases DVM increases. Lower temperatures are a proxy variable for ice and snow which slow traffic and reduce network capacity.
- Bus patronage - as bus patronage increases DVM also increases. This is somewhat surprising as it suggests that extra demand for travel is catered for by both modes, this is discussed in more detail in the next section.
- Working age population minus out of work benefit claimants (WAP-OWB) - as this metric increases DVM increases. This suggests that the more people economically active then the greater the demand for travel.
- Fuel Price - as fuel price increases DVM decreases. As the main non-fixed cost the laws of supply and demand dictate that as the costs of travel by a mode increases then demand will fall.
- Additionally, the season is shown to be relevant with autumn and winter shown as significant with respect to delay.

Gross household income was initially included in the model, however it was not statistically significant and did not improve the level of explanation and was thus removed.

In order to validate the above results the same data set was also analysed using an ARIMA model. This produced very similar results and it was decided the parsimonious model i.e. the Prais-Winsten regression model with AR(1) disturbance would be presented in this paper. Unfortunately, the need for brevity precludes a detailed discussion of the ARIMA approach but it does provide validation of the results presented here in.

6 DISCUSSION

In this section we discuss the results presented previously in this paper by placing them within the framework presented in Figure 2. However firstly it is important to keep in mind a number of limitations and resultant assumptions relevant to this research:

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\(^1\) The elasticity of DVM with respect to LWPP is calculated by using the term: $\frac{\partial}{\frac{\partial y}$
The availability and frequency of data placed some limitations on this research; firstly it was necessary to interpolate weekly values for a number of the variables, including the continuous intervention variable LWPP. Secondly, it was not possible to derive weekly values for Gross Value Added (GVA). Ideally one would have included this in the initial model as it is prominent in literature as a driver of congestion. However, as this research concentrates on congestion generated by peak period commuting, a variable measuring the number of individuals in work is preferred regardless of the practicalities of including GVA. The working age population minus the number of those claiming out of work benefits (WAP-OWB) is thus used as a more directly relevant macro-economic indicator.

Finally, it is recognised that, in utilising the WAP-OWB to represent the economic driver for demand for travel, the assumption is that, over the 5 year study period, the demographics of the WAP remain sufficiently similar so as not to change the overall propensity to choose any given mode of travel. Changes to the age structure and gender balance shown annually as part of the Annual Population estimates (20) were very small and it was concluded that this was only likely to impact DVM in the long term.

Before the results from the time series model are discussed a significant observation concerning the LWPP time series shown in Figure 1 should be noted; LWPP shows an initial fall of 17.5% prior to the introduction of the WPL and a subsequent more gradual fall to around 75% of its 2010 levels. This differs from the impact of the Perth Parking Space Levy which observed both a smaller initial decline in provision of around 10% as well as a subsequent rebound in levels of off street parking supply (14). Assumptions concerning the likely impact of the Nottingham WPL were based on these findings from Perth (21). Despite differences between the two schemes, this suggests that in a UK or European context, a WPL is likely to generate less revenue, but potentially be a more effective standalone tool for reducing congestion. The effects of seasonal variations to the number of LWPP can be observed with a slight rise in the number of LWPP at the end of each summer. As previously mentioned in Section 3 this seasonal pattern has been superimposed onto the interpolated data prior to 2012.

As indicated in the previous section the results reveal that that LWPP has a statistically significant impact on DVM. However the aim of this research was to evaluate the impact of the WPL on traffic congestion. In order to make this causal link to the WPL it is assumed that changes in the number of LWPP are a direct result of the introduction of the WPL. This assumption is considered sound given the relatively short study period of this research, however, in the long term other socio-economic and transport related factors may also influence this variable. The results from the time series model have also enabled us to draw conclusions as to both the scale of the impact and how it compares with other important exogenous variables which also impact DVM. The results show that, based on the elasticities calculated in the previous section for every 332 LWPP that were removed by employers in response to the introduction of the WPL, DVM was reduced by 0.4 seconds.

This represents a time saving for the last quarter of 2013 of just under 15 seconds per vehicle mile, a total time saving in 2013 across the network and time period used in this study of

\[ \beta \frac{X}{Y} \]

The elasticity of DVM with respect to the control variables in the form of \( \ln X \) is calculated by using the term: \[ \frac{\beta}{\gamma} \]

The elasticity of DVM with respect to the control variables \( X \) is calculated by using the term: \[ \frac{\beta \cdot \frac{X}{Y}}{\gamma} \]
1,146 days. This can therefore be seen as a useful contribution to congestion constraint and confirms the expectations expressed in the WPL Business Case (21).

These reductions in DVM need to be considered against a background of changes in the DVM time series driven by the other significant exogenous variables and thus it does not necessarily follow that an actual overall reduction in DVM will be observed but what is indicated by these results is that it was lower in 2013 than it would have been had the WPL not been introduced. It is thus important to understand how these exogenous variables are related to both the dependent and intervention variables. Figure 2 summarises the associations indicated by the results of this research. It also includes a number of variables which were not included in the model, either because suitable data was not available, or because they will only impact on DVM in the longer term, i.e. they change so slowly that it will take longer than the 5 year study period to influence congestion.

The relative impact of each variable on DVM illustrated in Figure 2 is taken from the elasticities contained in Table 2. We have used an ordinal scale with 3 categories; Strong where the variable’s elasticity w.r.t. to DVM is in excess of 1, Medium where it is between 0.5 and 1 and weak where it is less than 0.5. Using the above definitions LWPP is shown to have a ‘Medium’ impact. There are two exceptions to this approach; firstly because the Road Works Index is not a real world unit the elasticity produced does not reflect its actual impact which is estimated to be in excess of 5.5 seconds of DVM at their peak, the association is therefore shown as ‘medium’ in Figure 2. Secondly the seasonal variable is a categorical variable with four seasons (reference case= summer) and there is no difference in DVM between the summer season and the spring season. The values of the other coefficients (also known as differential slope coefficients) have been used as a proxy to determine the relative impact on DVM. The direction of the relationship is given by a ‘+ve’ or ‘−ve’ symbol in each box denoting positive or negative relationships with the dependent variable.

While an adjusted $R^2$ value of 0.62 shows that 62% of change in the dependent variable is accounted for by the set of independent variables included in the model this still leaves 38% of that will be due to variables not included in the model. While some of these will always be unknown it is possible to postulate what some of them may be based on the findings of the literature review in Section 2. These have been included in Figure 2 and are discussed below. VMT is not included within the model used in this research as it will be closely related to DVM and will be impacted by almost all of the explanatory variables.
FIGURE 2 Influence of independent variables on Delay per Vehicle Mile

KEY

Dependent Variable

VMT-ve = Vehicles Miles Travelled (capacity constrained)
VMT+ve = Vehicles Miles Travelled (unconstrained by capacity)

Independent variable not directly included in the model
Independent variable included in model

Degree of impact indicated (Elasticity Range)

\[ \rightarrow \] Strong (>1)
\[ \rightarrow \] Medium (0.5-1)
\[ \rightarrow \] Week (<1)
\[ \rightarrow \] Postulated

Variables primarily impacting travel demand

- Local cost of travel by public transport
- Changes to demographics of working age
- Induced/generated traffic
- Long term changes to network capacity
- Fuel Price (-ve)
- Public Transport Patronage (+ve)

Variables primarily impacting supply (Network Capacity)

- Economic factors e.g. GVA, Household Income
- Introduction of WPL
- Season (+ve for Autumn and Winter relative to Summer)
- Total Working Age Persons not claiming out of work benefits
- Index of disruption by roadworks (+ve)
- Average monthly minimum temperature (-ve)
- LWPP (+ve)
It will be positively related to DVM where network capacity has not yet been reached as it will reflect the demand for travel. However, if a network is at or close to capacity the relationship may be negative when roadworks, permanent network changes or inclement weather reduce the capacity or an increase in demand leads to a break down in flow as the network reaches capacity. This latter effect is demonstrated by traditional speed flow curves. Figure 2 illustrates this by differentiating VMT as +ve or –ve and relating this to the other independent variables. GVA and variables relating to the demographics of the working age population were discussed at the start of this section; both are included as variables in Figure 2 along with postulated links to DVM and other variables.

An additional observation can be made concerning the relationship between public transport patronage (PT) and DVM. A reliable time series of the local cost of travel by public transport was not available so public transport patronage is used as a variable to represent the attractiveness of public transport as shown in Figure 2. It would initially be expected that there would be a negative relationship between these two variables, however, this research reveals that there is a positive relationship at a statistically significant level, i.e. if congestion increases so does PT patronage. This implies that any increase in demand for travel is thus catered for by both private car and PT. However, there will be a point when PT capacity expands, as road network capacity remains constant or slowly declines, that any additional demand for travel must be absorbed by PT or active modes.

7 CONCLUSIONS

The impact of Nottingham’s Workplace Parking Levy on levels of morning peak period congestion was analysed using a Prais-Winston regression model with AR1 disturbance applied to weekly time series data for Delay per Vehicle Mile (DVM). Liable Workplace Parking Places (LWPP) was used as an independent continuous intervention variable. Based on a literature review of exogenous factors likely to impact on congestion, indicators of economic performance, population, weather, network disruption due to roadworks, fuel price and public transport patronage were identified to be included as time series within the model as control variables alongside the intervention variable. This approach thus accounts for external contextual changes which may obscure the impact of the WPL on congestion.

Model output indicates that the introduction of the WPL has had a statistically significant impact on congestion in Nottingham. The results show that the reduction in the provision of LWPP would, if all other explanatory variables remained constant, reduce Delay per Vehicle Mile (DVM). It is shown that the elasticity of DVM with respect to LWPP is 0.55, i.e. a 1% reduction in the quantity of LWPP explains a 0.55% reduction in congestion. This confirms the hypothesis proposed in the Methodology Section of this paper:

“The fall in LWPP from 2010 and early 2012 has contributed to the observed reduction in DVM from late 2010 to mid 2012”

Additionally the model also shows that the following had statistically significant impacts on DVM:
• An increase in the number of people of working age who are not claiming out of work benefit will result in a rise in DVM

• Cold weather. A lower mean minimum temperature will result in a rise in DVM.

• A rise in fuel price will result in a fall in DVM.

• Disruption to the network due to roadworks. The more road work disruption the network experiences the higher the DVM.

Of these variables the number of people of working age who are not claiming out of work benefit is shown to have the most impact on DVM. While although LWPP (i.e. the introduction of the WPL) is perhaps less influential than this macroeconomic variable, it does never the less still have an important impact and thus contributes to congestion restraint. These results show that while the WPL contributed to the reduction in DVM observed in 2011 further ongoing beneficial impact has been obscured by external explanatory variables, particularly the high levels of roadwork activity from 2012 onwards.

The findings of this research are highly significant as it is the first time that evidence has been presented for a statistically validated link between the introduction of a WPL and a reduction in congestion. This will have implications for the transferability of the approach taken in Nottingham to other UK and World Cities as it demonstrates that a WPL can be an effective tool in the transport planner’s armoury when it comes to constraining congestion.

Additional research is required as to the long term impact of suppressed demand for travel by car (stemming from both affordability issues and due to current levels of congestion) on the ability of measures such as the WPL package to restrain congestion while contributing to expanding public transport provision/capacity and to achieve favourable differential change relative to comparable Cities. Furthermore, it is recommended that future research should also aim to apply a similar time series modelling approach to the impact of the WPL package as a whole including the public transport improvements on levels of congestion in Nottingham.

REFERENCES


