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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/pupils. 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 (NET Phase 2), 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 traffic congestion in Nottingham. Hamer et al. (2009) 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

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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.

2.1. Defining and measuring traffic congestion

Traffic congestion is inherently difficult to define; it often has different meanings or definitions depending on the individual or organisation (Wang, 2010). The UK Department for Transport (DfT) (2016), notes that congestion can be said to have both physical and relative dimensions. In a rural setting any queue at a junction may be unexpected and thus be considered as congestion whilst commuters in a more urban setting consider this the norm even though the actual time spent queuing would be much greater. In this urban setting only an excessive delay at that junction may be considered as congestion by a commuter. Thus perceptions of congestion are relative (DfT, 2016). Its physical characteristics occur when vehicles interact with other vehicles and road users to produce a slower speed than would be expected if only one vehicle was using the road (DfT, 2016).

Various academic sources attempt to provide a definition based on the physical dimension. For example Goodwin (2004) defined congestion as “the impedance vehicles impose on each other, in conditions where, due to the speed flow relationship the use of transport system approaches its capacity” while Brownfield et al. (2003) defined congestion as “An urban or peri-urban link is defined as being congested where the point average speed taken over 3 min is below 50% of the speed limit”.

Additionally various researchers, for example, Skabardonis et al. (2003) and Dowling et al. (2004), divide congestion into recurrent and non-recurrent types. Recurrent congestion is that caused by regular events such as times of high demand for travel whilst non-recurrent congestion is that caused by one off events such as accidents.

For this research it is necessary to quantify congestion in order to assess change over time therefore it will be the physical dimension that must be the focus. As most measures of congestion utilise journey times averaged over a period of time they inevitably contain elements of both recurrent and non-recurrent congestion as it is difficult to separate out the two components from the data sets.

In the UK the consensus amongst Local Authorities and the DfT is that traffic congestion can be defined as a state where the speed on a given stretch of road falls below the free flow speed. The DfT (2009) defines congestion on UK major roads as vehicle delay which is the difference between the actual travel time and a reference travel time i.e. the journey time possible under free-flow conditions.

Having arrived at a suitable definition of traffic congestion it is now necessary to review the available literature to understand the metrics which have been used to measure levels of traffic congestion. The advent of data generated from GPS from satellite navigation systems has enabled the use of time based metrics thus rendering the use of flow as a proxy for congestion as obsolete. A number of such physical, time based metrics are discussed below.

Taylor et al. (2000) outlined a measure he termed the Congestion Index (CI), this is a measure that is often quoted in academic papers, for example Wang (2010). This compares total travel time on a link as a proportion of expected free flow travel time. A CI of 1 would indicate zero congestion whilst an index close to zero would indicate high levels of congestion. Wang (2010) observes that as this metric is dimensionless and thus not dependent on link length it can be used for comparison across segments, corridors or even large networks. This has a disadvantage as the figure it produces is essentially abstract in that it does not relate to a real unit of measurement i.e. time lost.

The UK Commission for Integrated Transport recommended that a measure of congestion be based on the difference between free flow speed and actual speed (DfT, 2000a). This indicator was more fully defined in the follow up report “A measure of road traffic congestion in England” (DfT, 2000b). This concept has become known as delay and was used by the DfT as a congestion metric for UK Major Roads (the Strategic Road Network) until 2010 (DfT, 2009). The US Department of Transport Guidance for measuring effectiveness for highway schemes defines a similar measure which calculates delay per vehicle mile travelled (US DoT, 2013).

Grant-Muller and Laird (2006) have note that there are 2 main drawbacks to these delay based indicators:

1. They fail to take into account the impact of journey time variability
2. Where they are expressed per vehicle, no allowance is made for vehicle occupancy.

The latter has obvious ramifications for urban congestion monitoring as it is possible for delay per vehicle to increase while delay per person is falling due to the prioritisation of public transport.

Journey time variability is a different concept to all the measures of congestion discussed so far in that it quantifies the amount of uncertainty or variability faced by a traveller considering a journey. It does not quantify absolute delay, therefore, a traveller may experience a great deal of delay but provided that the overall journey time doesn't vary much from day today this metric would have a relatively low value (DfT, 2016). Because of this Journey Time variability is not suitable for this research problem as the aim of this research is to assess change in congestion over time.

Given that there is a general preponderance of metrics described in this literature review based on the concept of delay it would seem reasonable to use a delay based metric. Although the benefits of assessing congestion on the “person” level rather than vehicle level is recognised, there is currently no local data set available that would enable the calculation of this metric.

Therefore, average delay per vehicle mile was chosen as the metric for quantifying congestion in this research.

2.2. 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 (Dale et al., 2013). 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 (1983) 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 (TfL, 2012). 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 (DfT, 2013): (i) population growth, (ii) GDP per capita/disposable income and (iii) the cost of motoring.

DfT (2013) 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 (DfT, 2015). The DfT identifies weather conditions as being an important factor, for example, wintery 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. (2014) 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.

2.3. Parking space levies world wide

In order to place the research presented in this paper in context it is important to have an overview of similar schemes to the Nottingham WPL elsewhere in the world.

Legorreta and Newmark (2015) conducted a review of similar parking space levies worldwide summarising their key characteristics. While they define PSL's as a "special property tax charged on non-residential off-street parking" a closer examination of the 11 schemes that they identify reveals that only Nottingham, Perth, Sydney, Melbourne and Singapore actually impose a regional levy on each parking place. The other schemes are either national income tax based or are a charge on parking area. In Singapore the levy is so low (US\$7.40 per space per year) that it can be seen as largely symbolic (Legorreta and Newmark, 2015).

Table 1 summarises the characteristics of the three Australian PSL schemes alongside the Nottingham WPL.

Table 1 highlights significant differences between the four schemes. It is important to note that Nottingham is the only scheme exclusively aimed at workplace parking provided by employers.

All four schemes are primarily aimed at targeting traffic congestion, via both the pricing element, as well as investment of the revenue raised back into public transport infrastructure.

The similarities between elements of the Perth and Sydney schemes and the WPL in Nottingham reflect that the two Australian schemes were used as models for the development of WPL in the UK.

The Nottingham WPL Scheme has significant differences to other schemes elsewhere; additionally the geographical and cultural setting of Nottingham is very different to that of the Australian examples with respect to the proximity of competitor cities and a different legislative background. These differences suggest that any assumptions as to the impact of the Nottingham WPL based on existing experience are questionable.

2.4. The impact of workplace parking levies on congestion

A number of researchers (Hamer et al., 2009; Young et al., 2013; Marsden, 2006) have identified some barriers to carrying out comparisons between area wide parking charge schemes. Such schemes are seldom introduced in isolation as the revenue is usually used to implement a package of transport demand management measures which can

vary from scheme to scheme (Hamer et al., 2009). This then causes two problems:

1. It is difficult to isolate the effect of the charging scheme from that of other measures (Hamer et al., 2009; Young et al., 2013).
2. The packages can vary significantly from scheme to scheme (Marsden, 2006).

Richardson (2010) studied the outcome in Perth; he reports that following introduction, parking supply contracted by 10% before slowly rebounding, but not recovering to pre 1999 levels. This is contrary to the pre 1999 trend of steadily increasing parking supply.

Clearly a reduction in workplace parking supply is not a guarantee that congestion will decrease. However, Richardson (2010) presents figures from the Australian Bureau of Statistics for Perth which shows that there has been a significant shift in mode share. Prior to implementation only 35% of journeys to work were on public transport; however by 2010 this had risen to over 50%, while car mode share had fallen by a similar amount clearly demonstrating a mode shift to public transport. Indeed public transport use grew by 67% in the 10 years from 1999 to 2009. Richardson (2010) 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.

While these figures are positive, Richardson (2010) does not present any data to benchmark these against other similar cities. It can be concluded that, while the results of this investigation are encouraging, further benchmarking and corroborative research is required to show causal attribution of the encouraging trends in mode share to the Perth PSL. It is important to note that, over a decade after the introduction of the PSL, Perth is still struggling to overcome traffic congestion due to a booming economy and a large population increase (Martin, 2012). Thus the literature suggests that while the Perth Parking Levy has affected both mode shift and an initial drop in traffic levels, these benefits are being obscured by continued economic growth. Hamer et al. (2009) carried out a review of the outcomes from the Melbourne CBD parking levy. They conclude that although the total number of trips to the CBD has remained stable, the number and proportion of cars entering the charging area has fallen. However, they conclude that the levy is having only a minor impact on congestion. Young et al. (2013) carry out a more recent review of the impacts of the Melbourne scheme and conclude that the impacts appear to be positive in respect of mode shift and a decline in the supply of parking spaces. However they also acknowledge that changing economic and policy factors obscure the extent of the impact of the PSL scheme. Monitoring data for Sydney appears to be sparse (Enoch and Ison, 2006). According to the New South Wales Ministry of Transport 70% of all trips to Sydney are by car (New South Wales Ministry of Transport, 2003). This is used as justification for the Parking Space Levy. Enoch and Ison (2006) argue that, as 85% of all traffic entering Sydney is through traffic and that as 460,000 vehicles travel in the city with only 36,000 chargeable spaces, the impact of the PSL on congestion is likely to be minimal. More recently Ison et al. (2013) conclude that the Sydney PSL has not resulted in a reduction in the supply of parking spaces and that it is not clear as to whether it has had an impact on congestion which remains a problem for Sydney.

The above discussion shows that Perth has seen the most positive results with respect to congestion and mode shift. However, all three Australian schemes lack a comprehensive evaluation in that there is no research which directly links the observed changes in these important indicators to the PSL schemes.

2.5. 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. (2002) used a least-squares regression model to

Table 1
Summary of area wide parking place levy schemes.

Location	Area	What's Liable for charge					Introduced	Main Exemptions	Revenue in 2014	Charge per place	Objectives	Uses Of Revenue
		General Description	On Street Parking	Public Car Parks	Un occupied Spaces	Small Business						
Perth Parking Licence Fee	Central Business District (CBD)	All non-residential parking bays that are in use	YES	YES	NO	NO	1999	Disabled spaces, Loading bays, Public service spaces Spaces incidental to primary business activities, Businesses with less than 6 spaces.	A\$34m	Long Stay: A\$1132, Short Stay: A\$1050 (2017)	Cut congestion by effecting modal shift and fund Central Area Transit bus system	Hypothecated for Transport - Central Area Transit bus system and the expansion of the Free Transit Zone
Sydney Parking Space Levy (PSL)	CBD + five other outlying business areas	Off street private non-residential parking, occupied or un- occupied, does not apply to public car parks.	NO	NO	YES	YES	1992	Disabled spaces, Loading bays, Public service spaces, Spaces incidental to primary business activities. Retail, restaurant, hotel parking, is exempt in outlying areas	A\$99m	A\$2840 CBD and North Sydney, A\$2350 in other areas (2017)	Discourage car use Use revenue to fund infrastructure to encourage public transport use.	Hypothecated for Transport Infrastructure: Interchanges, Bus/Rail/ Ferry, Park and Ride, Rapid Bus Transit way bus stations, light rail and electronic passenger information systems
Melbourne Congestion Levy	CBD	All public and private long stay non-residential car parking spaces currently in use	NO	YES	NO	YES	2006	Business Visitors, Emergency vehicles, Council and charities, Spaces incidental to primary business activities	A\$48.2m	A\$1380/ A\$980 (2017)	Reduce Traffic Congestion via encouraging public transport use by commuter and create more car parking for shoppers and visitors	Not hypothecated - some but not all of the revenue was used for public transport improvements
Nottingham Workplace Parking Levy	City of Nottingham	Occupied private non-residential off street workplace parking	NO	NO	NO	NO	2011	Emergency Services, Frontline NHS services, Employers < 11 spaces, Customers, Disabled spaces Loading bays	£9m	£379 (2017)	Constrain congestion, encourage modal shift to sustainable modes and Fund transport Infrastructure	Hypothecated for Transport - Light rail expansion, Link buses and the redevelopment of Nottingham Station

Sources: NCC (2008), NCC(2012), Enoch (2001), Richardson (2010), Hamer et al. (2009), State Revenue Office Victoria (2017), Transport for NSW (2017), Legorreta and Newmark (2015) and DoT (2017).

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. (2007) utilised an alternative time series analyses capable of compensating for serial autocorrelation 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. (2012) 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. (2014) 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. ARIMA differs from DiD in that it is a 'pattern matching' model rather than one which makes use of comparisons, utilising linear regression, between a before and after period and a control group and one subject to the intervention.

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 Prais-Winsten Regression models, ARIMA models and DiD estimation are all options. DiD was ruled out as congestion data for a control area was not available. While ARIMA remained an option it was decided to use the Prais-Winsten regression model with AR(1) disturbance as this provides easily interpretable and flexible output. While more parsimonious than ARIMA, this model was shown to be a good fit to the data and was capable of correcting for autocorrelation. Furthermore, as noted by Shmueli (2010), pattern matching models such as ARIMA are less suitable for testing causality, which is a requirement of this research. The following section outlines this chosen statistical approach.

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.

3.1. 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 min.

3.2. 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. There are two primary mechanisms by which the introduction of a WPL will impact the quantity of parking provided at the workplace to commuters (Dale et al., 2015):

1. Direct increase in cost in commuting to work by car due to Workplace Parking Charges. Some employers choose to pass on the cost of the provision of these places to their employees. In 2016 53% of workplace parking places liable for the WPL charge were covered by employer run parking management schemes which pass the cost of the WPL onto their employees thus effectively increasing the cost of commuting to work by car. Prior to the WPL few, if any, of the employers in the City charged employees for parking at work. According to basic economic theory this should decrease the demand for parking.
2. Decrease the supply of Workplace Parking. The WPL prompts employers to 'ration' the parking places they provide to employees in order to limit their WPL liability causing a contraction in the supply of parking places. There is considerable evidence of this from the larger employers, for example Nottingham Trent University redeveloped one of their City Centre Car Parks shortly after the introduction of the WPL.

Thus the intervention variable 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.

WPL licencing data from April 2012 to December 2013 shows that WPP fell from 44,333 to 42,235 a similar absolute reduction to that observed in the LWPP in the same period suggesting that the reduction in the supply of WPP is influenced by the charge imposed on LWPP.

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. This is detailed in Table 2.

To reflect this assumption the weekly values between the 2010 OSPA data point and first availability of licencing data in September 2011 have been estimated by using a non-linear interpolation so as to produce a time series for this period that shows the fall in LWPP accelerating the closer one gets the introduction of WPL. This approach is considered more accurate than applying linear interpolation but is, never the less, a representation of the most probable pattern of change based on the qualitative data presented in Table 2.

Finally, the seasonality observed in 2013 and 2014 was superimposed on the interpolated LWPP data prior to September 2011. The normal method of applying seasonal indices based on a moving average was used to achieve this. It should be noted that dummy variables for each season are included in the model to account for seasonality within the dependent variable. (See Table 3).

Fig. 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.

3.3. 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 and the dependent variable are listed and specified in Table 3. Importantly this table also identifies the frequency with which the variable is reported and how it has been interpolated to a weekly value.

4. Methodology

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 (TfL, 2012). 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.

Fig. 1 in the previous section 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.*

There was a steep reduction in LWPP provision in the year prior to licencing and there has been a more gradual decline since. The steep fall in LWPP between 2010 and late 2011 can be validated by examining the behaviour of the larger LWPP providers on an employer by employer basis. This analysis shows that the largest 30 providers cut their WPP provision by 20% in that period.

As discussed in section 2, two statistical models that can be used to achieve the study aim are: Prais-Winsten regression and ARIMA models. An 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.

The variables LWPP and working age population-out of work benefit claimants are several orders of magnitude larger than the dependent variable. Additionally it was unclear if they are linearly related to the dependent variable. These variables have thus been transformed logarithmically prior to inclusion within the model.

4.1. Model specification

Initially a simple linear-log model was employed given by

Table 2
Employer Actions impacting workplace parking 2010–2012.

Employer	Date of action	Actions
Nottingham City Council	July 10 to Feb 2011	NCC consolidated into a City Centre building where car parking for staff was reduced
Nottingham City Council	Spring 2011	NCC engages with employers to explain the WPL Scheme
Nottingham City Council	Sep 2011	Introduced parking management- Charging for staff parking
Boots		Introduced parking management- Charging for staff parking
University of Nottingham	Sep 2011	Introduced parking management- Charging for staff parking
Nottingham Trent University	Late 2011	Introduced parking management on Clifton Campus – No student parking allowed
Nottingham Trent University	Mid 2012	Redeveloped city centre car parks into office space
Eon	Late 2011	Consolidated into a City Centre building where car parking for staff was reduced
New College Nottingham	Nov 2012	Introduced parking management
Imperial Tobacco	Apr 2012	Introduced parking management- Charging for staff parking

Table 3
Description of variables.

Variable	Unit	Weekly average (2009–2013)	Standard Deviation of Weekly Data	Frequency of measurement	Level of geographic aggregation	Time Period	Method used to interpolate weekly time series	Source	Notes and Justification for inclusion in model
Delay per Vehicle Mile	minutes	1.22	0.24	15 min intervals	Greater Nottm	07:00–10:00	No interpolation required	TrafficMaster	This is the dependent variable.
Rainfall	mm	11.17	6.36	365 days per year Monthly	Area	NA	Monthly value applied to each week in that month	Met Office Station at Sutton Bonnington	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: $\text{RainMnth}/(((365-28)/11)/7)$, Except Feb which is calculated by: $(\text{RainFeb}/4)$
Average minimum temperature	deg C	6.12	4.24	Monthly	Area	NA	Monthly value applied to each week in that month	Met Office Station at Sutton Bonnington	This is an important as a proxy for wintery weather such as snow and ice which both slows traffic speed and reduces traffic flow.
Working age population minus Total Out of Work Benefit Claimants	persons	370,337	4758	Annual/ Quarterly	Greater Nottm	NA	Linear Interpolation	Office for National Statistics (ONS)	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.
Index of roadwork activity	Scale of impact; 0 - 12	1.34	2.62	Weekly	Greater Nottm	NA	NA	Nottingham City Council 2012	A road works index was compiled to quantify disruption to traffic caused by the construction phase of the following major transport improvements: <ul style="list-style-type: none"> • 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.
Fuel Price	pence per litre of unleaded	124.26	14.71	Monthly	UK	NA	Linear Interpolation	http://www.petrolprices.com/ the-price-of-fuel.html	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.
Season Public Transport Patronage	Dummy Variable Journeys (millions)	NA 1.44	NA 0.07	NA Quarterly	NA Greater Nottingham	NA 00:00–23:59	NA Quarterly figure divided by 13 and applied to each week in the quarter	NA Nottingham City Council 2012	This is a dummy variable 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.
Introduction of the Nottingham WPL	Liabile Workplace Parking Places	29,984	3049	April 2010, then Sep 2011 then monthly from 01/04/2012	Nottingham City	NA	Non-linear Interpolation	Nottingham City Council 2012	Number of Workplace Parking Places in Nottingham which are liable for the WPL charge.

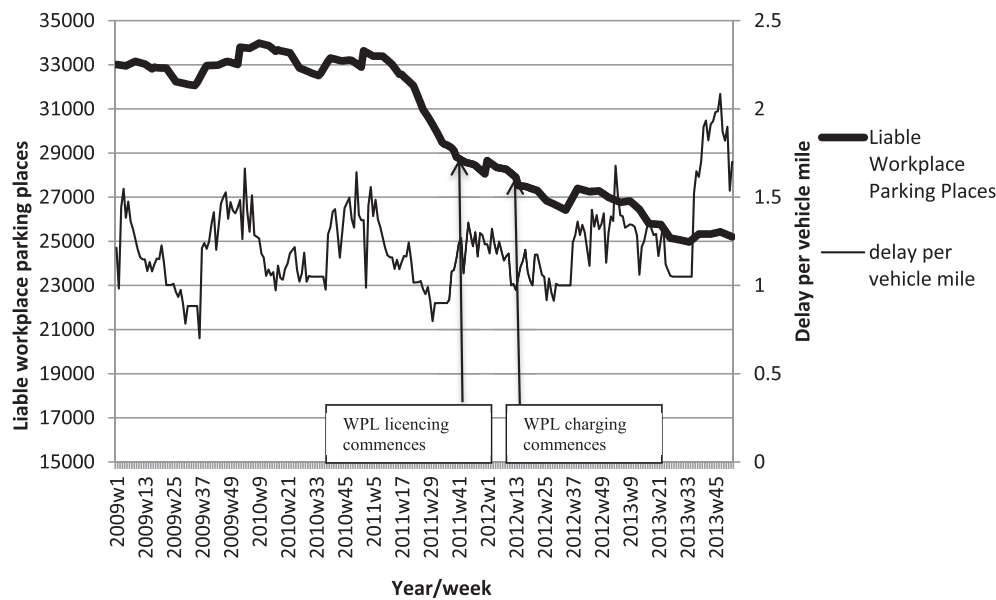


Fig. 1. Delay and workplace parking places.

$$y_t = \alpha + \beta_k X_t + \gamma \ln LWPP_t + \theta_m D_t + \varepsilon_t \quad (1)$$

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, ε is white noise. β , γ and θ 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-Winsten regression model should be employed. This issue is discussed and evidenced in the results section of this paper. In this model, the errors are assumed to follow a first-order autoregressive AR(1) disturbance as shown below:

$$\varepsilon_t = \rho \varepsilon_{t-1} + e_t \quad (2)$$

where ρ ($-1 < \rho < 1$) is the autocorrelation coefficient, and e_t is independent and identically distributed with zero mean and a constant variance σ^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 (Prais and Winsten, 1954).

Tests showed there is some multicollinearity between LWPP and Working age population - out of work benefit claimants (WAP-OWB). As a result we temporarily removed WAP-OWB to determine if this altered the results with respect to the impact of intervention variable on the dependent variable. This showed that the model results remained largely unchanged however the adjusted R^2 did reduce with the omission. As the presence of multicollinearity is not in itself a restrictive assumption provided it does not impact the model results we do not consider this an area of concern for the model specification and have thus included WAP-OWB within the model.

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. adjusted R^2 value of 0.80), 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 (Durbin-Watson d -statistic = 1.46). Therefore, the coefficients from the linear model may not be appropriate to evaluate the impact of the intervention. Subsequently, the Prais-Winsten regression model with AR(1) disturbance was employed. The results are presented in Table 4. The model goodness-of fit, the adjusted R^2 , is 0.62 which is very good for this type of model and commensurate

Table 4
Model results.

DVM	Coefficient	t	P > t	Elasticities of DVM w.r.t. Independent Variable
Continuous Intervention: log _e of LWPP	0.6735	3.48	0.00	0.55
Fuel price	-0.0038	-2.51	0.01	-0.39
Mean weekly minimum temperature	-0.0145	-3.1	0.00	-0.07
Weekly rainfall	0.0023	1.53	0.13	0.02
Winter	0.1263	2.72	0.01	NA
Spring	0.0339	0.89	0.37	NA
Autumn	0.1484	4.73	0.00	NA
Log _e of WAPmOWB (Working age population - Out of work benefit claimants)	7.9138	3.05	0.00	6.47
Roadworks index	0.0427	5.21	0	0.05
Bus Patronage	0.6117	3.2	0.00	0.72
Constant	-107.6624	-3.2	0.00	NA
Autocorrelation coefficient (rho)				0.33
Adjusted R-squared				0.62
Number of observations				260
Durbin-Watson d-statistic (Transformed)				2.04

with similar work (Hahn et al., 2002). 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 value of the autocorrelation coefficient (ρ) was found to be 0.33 indicating that the errors are serially correlated and the application of the Prais-Winsten regression model is appropriate. The Durbin Winsten d -statistic of 2.04 demonstrates that the model has successfully compensated for serial correlation by applying the Prais-Winsten transformation.

Having established the model is a good fit to the data, an examination of the regression co-efficients and their statistical significance can now be undertaken.

The fitted model is: (see Table 4):

$$\text{DVM} = -107.6624 + 0.6735\ln\text{LWPP} - 0.0038\text{FuelPrice} - 0.0145\text{MinTemp} + 7.9138\ln\text{WAP-OWB} + 0.0427\text{RoadWrks} + 0.6117\text{BusPat} + 0.1484\text{Autum} + 0.1263\text{Winter} + \epsilon_t \text{ where } \epsilon_t = 0.3254\epsilon_{t-1} + e_t$$

Table 4 shows that LWPP has a statistically significant impact on DVM at the 5% significance level indicating 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 is calculated at their means and found to be 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.
- 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 and, as the network capacity for general traffic remains the same, this in turn acts to increase DVM.
- 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.

6. Discussion

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

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 would have been optimum to included GVA in the initial model as it is prominent in literature as a driver of congestion. However it was not possible to do so as GVA is an aggregate value for a

year and thus there would have been insufficient distinct values in the time series to be used in this model. 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 included in the final model 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 (ONS, 2016) were very small and it was concluded that this was only likely to impact DVM in the long term. Thus they were not included in the model but are represented in Fig. 2 for completeness.

Before the results from the time series model are discussed a significant observation concerning the LWPP time series shown in Fig. 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 (Richardson, 2010). Assumptions concerning the likely impact of the Nottingham WPL were based on these findings from Perth (NCC, 2008). 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.

As indicated in the previous section the results reveal 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. As discussed in Section 3, a further assumption is that LWPP is a reliable proxy for Total WPP. As noted in Section 3 both WPP and LWPP saw a similar absolute reduction in the same period suggesting that the reduction in the supply of WPP is influenced by the charge imposed on LWPP. While this supports the above assumptions it should be noted that the percentage fall in Total WPP will be less than that in LWPP.

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,¹ for every 332 LWPP that were removed by employers in response to the introduction of the WPL, DVM was reduced by 0.4 s. This represents a time saving for the last quarter of 2013 of just under 15 s per vehicle mile, a total time saving in 2013 across the network and time period used in this study of 1146 days. This can therefore be seen as a useful contribution to congestion constraint and confirms the expectations expressed in the WPL Business Case (NCC, 2008).

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

¹ The elasticity of DVM with respect to the control variables in the form of $\ln X$ is calculated by using the term: $\frac{\partial \text{DVM}}{\partial \ln X}$. The elasticity of DVM with respect to the control variables X is calculated by using the term: $\hat{\beta}_X \frac{\bar{X}}{\bar{Y}}$

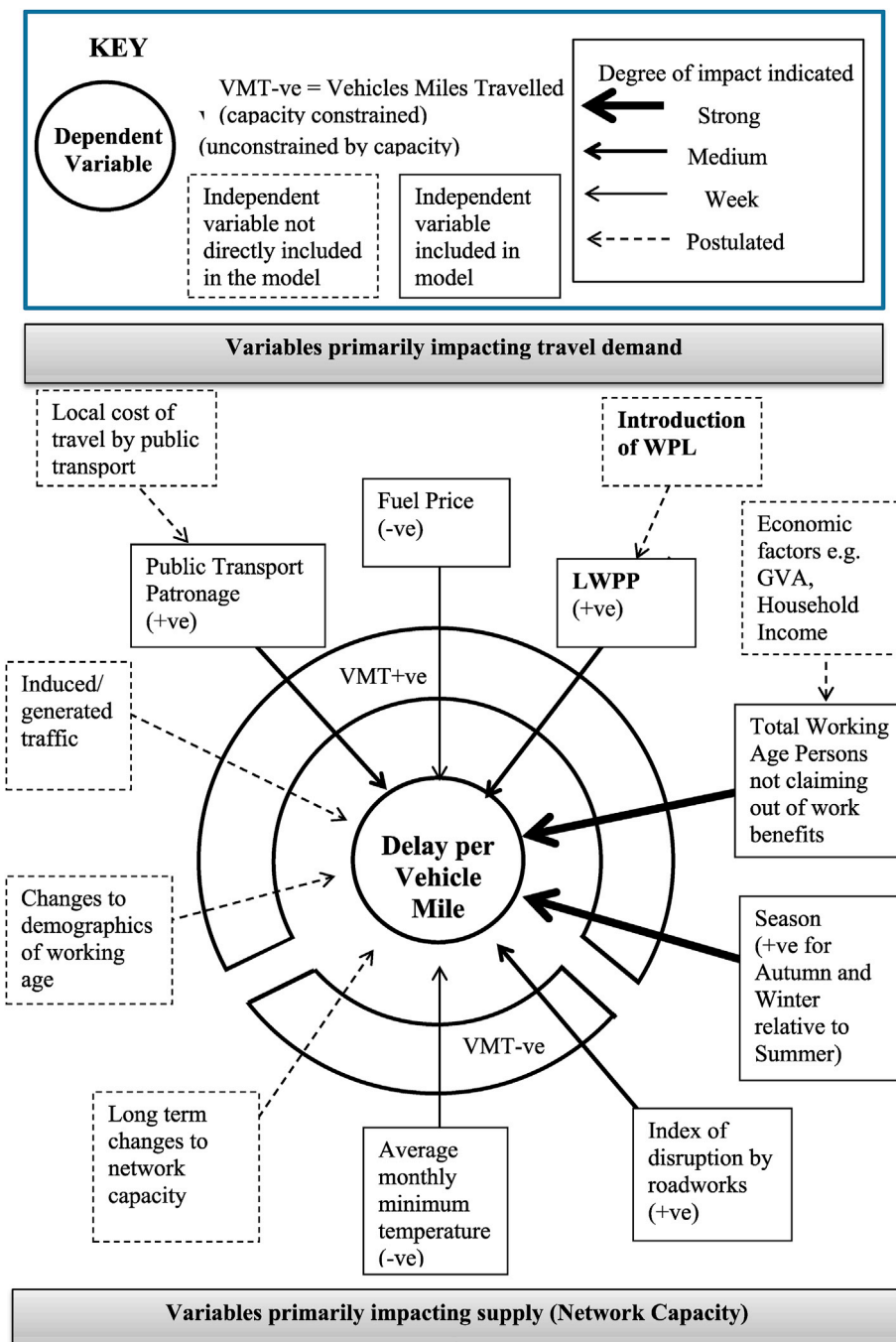


Fig. 2. Influence of independent variables on Delay per Vehicle Mile.

variables. Fig. 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 Fig. 2 is taken from the elasticities contained in Table 4. 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 s of DVM at their peak, the association is therefore shown as 'medium' in Fig. 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 variation in the dependent variable is accounted for by the set of independent variables included in the model this still leaves 38% 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 Fig. 2 and are discussed below.

VMT is not included within the model used in this research as literature suggests that it will be related to many of the other exogenous explanatory variables included in the model and thus DVM. Its inclusion would complicate the model and obscure the relationship between DVM and the other explanatory variables. Indeed, some measures of congestion used prior to the advent of GPS generated time based datasets used flow as a proxy for congestion.

VMT 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. Fig. 2 illustrates this by differentiating VMT as +ve or -ve and relating this to the other independent variables. GVA (Not included in the model for practical reasons) and variables relating to the demographics of the working age population (not included in the model as they have shown little change in the study period) were discussed at the start of this section; both are included as variables in Fig. 2 along with postulated links to DVM and other variables.

An additional observation can be made concerning the relationship between public transport (PT) patronage 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 Fig. 2. It may be initially expected that there would be a negative relationship between these two variables as the relative attractiveness of the private car and PT varies due to economic and cost factors, 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.

7. Conclusions

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.

The results from the Prais Winston Regression model show that the reduction in the supply of Liable Workplace Parking Places (LWPP) would, if all other explanatory variables remained constant, reduce Delay per Vehicle Mile (DVM). This demonstrates that the introduction of the WPL contributed to the reduction in congestion observed in 2011/12. Qualitative evidence suggests that the WPL achieves this impact by two mechanisms, firstly it applies an additional cost to commuting to work by car via employers passing on the cost of the WPL to their employees and secondly by a reduction in the supply of Workplace Parking Places as employers seek to reduce their WPL liability. Both mechanisms are manifested by a reduction in the intervention variable, LWPP.

However this research also reveals that this ongoing beneficial impact has been obscured by exogenous contextual factors; principally by an increase in both roadwork activity associated with the implementation of major transport improvements and the number of people of working age who are not claiming out of work benefits, a proxy for economic growth. The output from the model shows that both these variables are positively related to DVM and are thus placing an upward pressure on congestion. Literature suggests that economic growth increases the demand for travel while road work activity will reduce network capacity.

These findings 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.

Additionally this research highlights the need for organisations

seeking to implement a similar scheme to manage the expectations of stakeholders with respect to the impacts as changes to external variables can mask the beneficial impacts on 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. Although beyond the scope of this research from an academic perspective it may also be interesting to test the relationship between VMT and the other variables in Fig. 2 by substituting VMT for DVM and re-running the model presented in this paper.

References

- Department for Transport (DfT), 2015. Congestion on Local 'A' Roads, England. January to March 2015. Available on line at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/428634/congestion-local-a-stats-release-mar-15.pdf. (Accessed 6 June 2016).
- Brownfield, J., Graham, A., Eveleigh, H., Ward, H., Robertson, S., Allsop, R., 2003. Congestion and Accident Risk. Road Safety Research Report No. 44. Department for Transport, London.
- Cole, C., Qudus, M., Wheatley, A., Osmani, M., Kay, K., 2014. The impact of Local Authorities' interventions on household waste collection: a case study approach using time series modelling. *Waste Manag.* 34, 266–272.
- Dale, S.J., Frost, M.W., Ison, S.G., Warren, P., 2013. Workplace Parking Levies: the answer to funding large scale local transport improvements in the UK? In: 13th International Conference on Competition and Ownership in Land Passenger Transport, Oxford.
- Dale, S.J., Frost, M.W., Ison, S.G., Warren, P., 2015. Evaluating transport demand management interventions using theoretical evaluation. In: Transportation Research Board 94th Annual Meeting Compendium of Papers 2015 DVD. Transport Research Board, Washington.
- Department for Transport, 2013. Road Transport Forecasts 2013; Results from the Department for Transport's National Transport Model. Department for Transport (DfT). https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/212474/road-transport-forecasts-2013.pdf. (Accessed 6 June 2016).
- Department for Transport (DfT), 2000a. Tackling Congestion and Pollution: the Government's First Report. Department for Transport, London.
- Department for Transport (DfT), 2000b. A Measure of Road Traffic Congestion in England. Department for Transport, London.
- Department for Transport (DfT), 2009. Road Statistics 2008: Traffic, Speeds and Congestion. National Statistics, Department for Transport, London [online]. National Statistics.
- Department for Transport (DfT), 2016. An Introduction to the Department for Transport's Road Congestion Statistics [online]. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/527880/an-introduction-to-dft-congestion-statistics.pdf. (Accessed 7 July 2017).
- Department of Transport (DoT), 2017. Licensed Parking in Perth: a Guide for Commercial Property Owners about Licensing of Parking Bays for 2016-17. Department of Transport, The Government of Western Australia, Perth, Australia. Available online at: http://www.transport.wa.gov.au/mediaFiles/projects/PROJ_P_LicensedParkingPerthGuide.pdf. (Accessed 24 May 2017).
- Dowling, R., Skarbdonis, A., Carroll, M., Wang, Z., 2004. Methodology for measuring recurrent and non recurrent traffic congestion. *Transp. Res. Rec.* 1867 (1), 60–68.
- Enoch, M.P., 2001. Workplace Parking Charges Down under. *Traffic Engineering and Control*, pp. 357–360. November 2001.
- Enoch, M.P., Ison, S., 2006. Levying charges on private parking: lessons from existing practice. *World Transp. policy & Pract.* 12 (1), 5–14.
- Goodwin, P.B., 2004. The Economic Costs of Road Traffic Congestion. Discussion paper. Rail Freight Group, Transport Studies Unit, University College London, London. Available at: <http://eprints.ucl.ac.uk/archive/00001259/>. (Accessed 27 October 2012).
- Grant-Muller, S., Laird, J., 2006. Costs of Congestion: Literature Based Review of Methodological and Analytical Approaches. 2006 Scottish Executive. ISBN 07559 6306 7.
- Hahn, E., Chatterjee, A., Younger, M., 2002. Macro-level analysis of factors related to area wide highway traffic congestion. *Transp. Res. Rec.* 1817, 11–16.
- Hamer, P., Currie, G., Young, W., 2009. Exploring Travel and Parking Impacts of the Melbourne CBD Parking Levy. Australian Transport Research Forum 2009, Auckland, New Zealand, 32nd meeting.
- Ison, S.G., Mulley, C., Mifsud, A., Ho, C., 2013. A parking space levy: a case study of Sydney, Australia. In: Ison, S.G., Mulley, C. (Eds.), *Transport and Sustainability: Parking*, vol. 5. Ashgate. ISBN: 978-1-78350-919-5; (Chapter 14).
- Jia, Y., Wu, J., Qi, G., Du, Y., 2014. Impacts of rainfall weather on urban traffic in Beijing: analysis and modeling. In: Transportation Research Board 94th Annual Meeting Compendium of Papers 2015 DVD. Washington: Transport Research Board.

- Legorreta, A.M., Newmark, G.L., 2015. See spot taxed: the global experience with parking levies. In: 95th Annual Meeting of the Transportation Research Board, Washington DC, USA. January 2015.
- Li, H., Graham, D.J., Majumbar, A., 2012. The effects of congestion charging on road traffic casualties: a causal analysis using difference-in-difference estimation. *Accid. Anal. Prev.* 49, 366–377.
- Marsden, G.R., 2006. The evidence base for parking policies – a review. *Transp. Policy* 13 (6), 447–457.
- Martin, S., 2012. Stifling Success: Congestion Charges and Infrastructure Delivery. Committee for economic development of Australia, Melbourne [online]. <http://ceda.com.au/research-and-policy/research/2012/04/stifling-success>. (Accessed 19 February 2017).
- New South Wales Ministry of Transport, 2003. Parking Space Levy Review: Improving Public Transport. New South Wales Ministry of Transport, Sydney.
- Nottingham City Council (NCC), 2008. Workplace Parking Levy Business Case 2008. Nottingham City Council, Nottingham. April 2008.
- Nottingham City Council (NCC), 2012. WPL – Employer Handbook. Nottingham City Council, Nottingham [Online]. https://secure.nottinghamcity.gov.uk/wpl/common/Employer_handbook.pdf. (Accessed 19 February 2017).
- Office For National Statistics (ONS), 2016. Annual Mid-year Population Estimates: 2014. NOMIS database. <https://www.nomisweb.co.uk/>. (Accessed 6 May 2016).
- Prais, S.J., Winsten, C.B., 1954. Trend Estimators and Serial Correlation. Working paper 383. Cowles Commission. Available online at: <http://cowles.econ.yale.edu/P/ccdp/st/s-0383.pdf>. (Accessed 7 June 2016).
- Quddus, M.A., Carmel, A., Bell, M.G.H., 2007. The impact of the congestion charge on retail: the London experience. *J. Transp. Econ. Policy* 41 (1), 113–133.
- Richardson, E., 2010. Extracting maximum benefit from parking policy – 10 Years experience in Perth, Australia. In: European Transport Conference 2010, 38th edition. London: The Association for European Transport, Glasgow, Scotland, UK. October 2010.
- Shmueli, G., 2010. To explain or predict? *Stat. Sci.* 25 (3), 289–310.
- Skabardonis, A., Varaiya, P., Pretty, K., 2003. Measuring recurrent and non recurrent traffic congestion. *Transp. Res. Rec.* 1856 (1), 118–124.
- State Revenue Office Victoria, 2017. Congestion Levy Overview Web Page [online]. Melbourne, Australia. <http://www.sro.vic.gov.au/car-parks>. (Accessed 19 February 2017).
- Tanner, J.C., 1983. International Comparisons of Cars and Car Usage. Department the Environment and Transport and Road Research Laboratory, 1070. TRRL, Crowthorne, UK.
- Taylor, M.A.P., Woolley, J.E., Zito, R., 2000. Integration of global positioning system and geographical information systems for traffic congestion studies. *Transp. Res. Part C Emerg. Technol.* 8 (1–6), 257–285.
- Transport for London (TfL), 2012. Drivers of Demand for Travel in London: a Review of Trends in Travel Demand and Their Causes available online at: <http://content.tfl.gov.uk/drivers-of-demand-for-travel-in-london.pdf>. (Accessed 7 June 2016).
- Transport for New South Wales, 2017. Parking Space Levy Web Page. Transport for New South Wales, Sydney [online]. <http://www.transport.nsw.gov.au/programs/parking-space-levy>. (Accessed 9 February 2017).
- US Department of Transport (US DoT), 2013. Guide for Highway Capacity and Operations Analysis of Active Transport and Demand Management Strategies. Available online at: <http://ops.fhwa.dot.gov/publications/fhwahop13042/fhwahop13042.pdf>. (Accessed 14 April 2016).
- Wang, C., 2010. The Relationship between Traffic Congestion and Road Accidents: an Econometric Approach Using GIS. PhD Doctoral Thesis. Loughborough University.
- Young, W., Currie, G., Hamer, P., 2013. Exploring the impact of the Melbourne CBD parking levy on who pays the levy, parking supply and mode use. In: Ison, S.G., Mulley, C. (Eds.), *Transport and Sustainability; Parking*, vol. 5. Ashgate. ISBN: 978-1-78350-919-5;-(Chapter 13).