**Forecasting and valuing travel time variability for project appraisal**

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**Abstract**

This paper presents a study carried out as part of a contracted research project for Austroads. The study estimated a model for forecasting changes in travel time variability following the implementation of a transport scheme. To do this, the ‘UK model’ for travel time reliability (Hyder Consulting, Black and Fearon 2008) was re-estimated using data collected in Australia and New Zealand in 2015. The dataset contains observations on average travel times and standard deviations for 17,457 individual road segments within Australia and New Zealand cities. The results of the study show that the relationship is similar to the one found in the UK, but with differences in the magnitude of the effects of the variables. Finally, the study demonstrates how to use this relationship to forecast changes in travel time variability following the implementation of a transport scheme and how this can then be used to estimate a monetary value of reliability benefits for inclusion in transport appraisals.

**1. Introduction**

It has been widely recognised that travellers do not only take travel time into account, but also travel time reliability. In the presence of travel time unreliability, travellers typically allow more time for their trips in order to reduce the possibility of arriving late at their destination (de Jong and Bliemer 2015). Reducing the unreliability of travel time means that this extra time allowance could be decreased or avoided completely, presenting a clear user benefit which is distinct to the value of reduced average travel time. In project appraisal, excluding measures of reliability could lead to an understatement of the estimated economic benefits of transport initiatives. Similarly, it is important to take into account changes in reliability when forecasting the impact of a transport scheme on road user patronage.

Given the importance of travel time reliability, transport appraisal guidelines in Australia, New Zealand and overseas generally provide guidance on how to estimate and value changes in travel time reliability as a result of a transport schemes. However, in practice, travel time reliability is rarely included in cost-benefit analyses (CBAs) and road patronage forecasting.

Incorporating travel time reliability into CBAs or toll road patronage forecasting studies involves three main steps (de Jong and Bliemer 2015): (1) the derivation of the value of reliability; (2) forecasting the impact of infrastructure projects on reliability; and (3) incorporating road users’ responses to changes in travel time reliability.

This study mainly focuses on the second step, the estimation of changes in reliability as a result of the implementation of transport projects. This study provides a simple approach for estimating travel time reliability in line with contemporary practice and based on a comprehensive dataset of mean travel time and variability. The proposed framework could be used by practitioners in Australia and New Zealand within CBAs and transport demand forecasting studies. The approach allows appraisers to estimated changes in reliability when the only input known is the change in estimated average travel time and free flow travel time before and after the implementation of a project. Other, more sophisticated approaches to modelling reliability (within complex traffic demand models) are not considered here, but would be preferred in circumstances where they are available (for example, for very large projects) (de Jong and Bliemer 2015).

In this paper, the ‘UK model’ for travel time reliability (Hyder Consulting, Black and Fearon 2008) was re-estimated using data collected in Australia and New Zealand in 2015. The dataset contains observations on average travel times and standard deviations for 17,457 individual road segments within Australia and New Zealand cities. It has been collected through Google Maps in late 2015 for a large number of road segments in Australia and New Zealand.

The paper is organised as follows: Chapter 2 aims to define travel time reliability and presents the most commonly used models to measure travel time reliability. Chapter 3 presents the empirical analysis including the data used and methodology adopted. Chapter 4 provides guidance to apply the model of travel time reliability for project appraisal and road user patronage forecasting. A discussion of the empirical study is presented in Chapter 5, before Chapter 6 provides the conclusions.

2. Defining and measuring travel time reliability

2.1. Defining travel time reliability

Within the context of discussion and evaluation of travel time variability, a common decomposition of travel time is (Fosgerau et al. 2008):

Travel time = free flow time + systematic delay + unexplained delay

While the distinction between free flow time and delay is straightforward, the distinction between systematic and unexplained delay can be somewhat ambiguous and will depend on how much is known about the trip from the point of view of the traveller. From the traveller’s point of view, unexplained delay is everything that cannot be foreseen; such as additional travel time caused by random demand fluctuations or capacity reductions due to accidents. Wang (2014) posits that only delay caused by random fluctuations in demand (i.e., unanticipated congestion) and unanticipated incidents (i.e., accidents) should be included in measures of unexplained delay (and therefore travel time variability). A transport system with severe congestion may have stable day-to-day travel times (i.e., systematic delay); so travellers can anticipate and adapt to any systematic variation based on their past experience, so as to anticipate their arrival time. In addition, roadworks, extreme weather and special events, which may also cause delays, are considered to be predictable to some degree in that travellers can expect to be delayed in advance of making the trip. Also, a transport improvement has little impact on these causes and the effects on the base case and project case for a given evaluation tend to cancel each other out (Wang 2014).

In transport modelling, unexplained delay is represented by a random variable with a probability distribution, such that travel time varies randomly (Fosgerau et al. 2008). Travel time variability (and subsequently, reliability) in this context is most frequently defined as the random variation in travel time, i.e., the variation in unexplained delay (de Jong and Bliemer 2015; Carrion and Levinson 2012).

The majority of travel time variability studies have investigated day-to-day variations in travel time, and have explicitly defined travel time reliability as the random variation in travel time (see e.g., Hollander and Steer Davies Gleave 2009; Börjesson, Eliasson, and Franklin. 2012 de Jong and Bliemer 2015). The concept of variability purports that travellers have to make their decisions under uncertain circumstances with respect to the travel time; hence they are not able to predict the exact travel time or arrival time before starting their trips, given a departure time.

As a result of these behavioural complexities, a large number of measures of travel time variability have been developed in the literature. Nonetheless, a common feature is the recognition that travel time distribution is impacted by day-to-day fluctuations on the demand side (i.e., unanticipated variation in aggregate traveller’s demand for road usage) as well as the supply side of traffic (i.e., incidents that effect the normal flow or supply of road capacity) (Li, Hensher and Rose 2010).

2.2. Measuring travel time reliability

With regard to the effect of travel time unreliability on travellers’ utility, the literature most commonly assumes that:

* travellers experience inconvenience (disutility) from day-to-day variability in travel times as a result of the uncertainty in itself, no matter if one arrives early or late; and/or
* day-to-day travel time variability affects utility through scheduling considerations. That is, how often the traveller arrives late, and how late (or early) the traveller arrives on average.

Leading from these two assumptions, there are two general approaches to estimating value of reliability in travel times considered in the literature. As noted by Li, Hensher and Rose (2010), these involve either:

* distributional models of variance in travel times which rely on measures of disutility associated with mean and variance in travel times (or other associated distributional measures), otherwise known as ‘mean-dispersion models’; or
* models of scheduling delays that consider deviations from an individually determined preferred travel time (including late and early arrival and lateness at boarding).

3. Empirical study

This study was conducted on behalf of Austroads to assist in updating the National Guidelines for Transport System Management (NGTSM) (ATC 2006) with respect to the value of reliability. This study aimed to provide some interim guidance to Austroads that could be used while a full update of the guidance on the value of reliability is being undertaken. The interim guidance involved estimation of a new statistical model on the relationship between observed measures of congestion based on the UK ‘Arup model’ (Hyder Consulting, Black and Fearon 2008) and the standard deviation of travel time. This paper outlines the results from this analysis and sets out some interim recommendations.

This remainder of this chapter is set out as follows. Section 3.1 presents the data used to estimate the relationship between congestion and reliability for Australia and New Zealand. Section 3.2 outlines the model specification for this study and Section 3.3 presents the results from the empirical analysis.

3.1. Data

*3.1.1 Collection of data*

The empirical analysis presented in this paper is based on a large dataset collected by Deloitte from Google Maps during September and October 2015. It consists of observations of mean travel time and variability for a large number of road segments in from all Australian capital cities (Adelaide, Brisbane, Canberra, Darwin, Hobart, Melbourne, Perth and Sydney) and two cities in New Zealand, Auckland and Wellington.

More specifically, the data was obtained from Google Maps Distance Matrix Application Programming Interface (API), a web service[[1]](#footnote-1) that calculates travel distance and real-time “duration in traffic” for a given set of origin and destination coordinates. The origin and destination coordinates for the road segments were derived from geospatial “shape files” provided by state based road agencies. The Google Maps Distance Matrix API uses a “crowd sourced” approach to estimating travel time on roads based on data gathered from Android based mobile phones. The data is gathered by Google, and made available on their Maps product and associated APIs on a commercial basis.

Data was gathered at intervals of 15 minutes to an hour for 60 days during September and October 2015. More requests were made to the API during peak travel times to ensure that data during peaks was accurately captured. After gathering the data from Google Maps, a number of data improvement and cleaning tasks were completed. This included removing outlying or erroneous observations as well as adjusting for time zone differences between jurisdictions.

*3.1.2 Data preparation*

The data collected from Google Maps represented travel times in each city for all hours of the day. For this analysis, the data was restricted to peak hour morning traffic during the working week, between 7 am and 9 am, with the average travel time measured in 15 minute segments.

*3.1.3 Summary statistics*

In the UK, congestion index guidelines are based on a representative travel time for a journey. As the data track average travel times over a number of road segments, the modelling will assume that the relationship between travel times and variability is adequately represented at this level. To better capture the notion of variability over a commute, road segments were aggregated to the street level.

Key inputs to the UK model are the free-flow travel time and the travel time variability. The free flow travel time for a street was calculated as the average of the minimum travel time over the 24 hour period. Travel time variability is defined as the standard deviation of average travel time for each 15 minute segment between 7 am and 9 am.

In several cases, there was missing data at the road segment level for a given period. If this was the case, the travel time at the street level was estimated as an average of travel time for the same time segment at other points in the year. Table 1 below presents a summary of the key variables in each jurisdiction.

Table : Summary statistics for road segments in each jurisdiction

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Jurisdiction** | **Number of road segments** | **Average road segment distance (m)** | **Average segment travel time (s)** | **Minimum travel time (s)** | **Average speed (m/s)** |
| **Adelaide** | 548 | 2,408 | 306 | 247 | 8.82 |
| **Auckland** | 248 | 3,112 | 254 | 179 | 9.95 |
| **Brisbane** | 351 | 4,965 | 333 | 250 | 13.57 |
| **Canberra** | 118 | 6,884 | 399 | 316 | 14.3 |
| **Darwin** | 132 | 1,438 | 142 | 115 | 10.65 |
| **Hobart** | 130 | 1,533 | 129 | 97 | 10.96 |
| **Melbourne** | 461 | 4,050 | 409 | 288 | 9.93 |
| **Perth** | 76 | 15,084 | 902 | 699 | 14.75 |
| **Sydney** | 559 | 2,913 | 338 | 211 | 8.93 |
| **Wellington** | 125 | 3,458 | 221 | 170 | 11.92 |
| **Aus / NZ^** | **2748** | **3,679** | **329** | **239** | **10.47** |

*Source: Deloitte Access Economics analysis based on Google data*

*Notes: ^ This refers to the (unweighted) average across cities in New Zealand and Australia listed in Table 1.*

Variability in average travel time across the day implies that the impact of road upgrades should be proportional to the relative amount of traffic congestion. Figure 1 presents the average travel speed by jurisdiction distinguishing by three groups (group 1 being Sydney and Melbourne, group 2 representing Perth, Brisbane, Adelaide and Auckland and group 3 including Darwin, Wellington, Hobart and Canberra). As expected, there are clear troughs in average travel speed around 8 am and 5 pm. Adelaide has the slowest average speed of 28km/h, largely influenced by the very slow average speeds on King William St and North Terrace, and the types of roads in this urban area compared with other jurisdictions.

Figure : Average Speed



*Source: Deloitte Access Economics analysis based on Google data*

Changes in the variability of traffic times are also an important factor to consider. As Figure 2 suggests, this variability is correlated with average travel speed. Around the peak times, both average traffic speed and the average traffic variability are at their highest. Hence, it would be expected that improvements to reduce average travel times would also reduce variability in average travel time.

Figure : Travel time variability



*Source: Deloitte Access Economics analysis based on Google data*

3.2. Model specification

This section sets out the specification of the model used in the empirical analysis presented in this paper.

*3.2.1 UK congestion model*

The UK model was first developed and estimated by Arup (2003) using London and Leeds data collected in 1993 and 2003, respectively. In 2007, Hyder Consulting in collaboration with Ian Black and John Fearon were commissioned by the Department for Transport to further develop the relationship using a wider sample of urban roads. The re-estimated formula is recommended in the UK Transport Appraisal Guidelines (DfT 2014). Data used to estimate the formula is based on a sample of trips undertaken in the ten largest urban areas in the UK over a three year period (see Hyder Consulting, Black and Fearon (2008) for a description of the data used and model estimated).

The Arup model predicts variability from day-to-day variation in traffic conditions and incidents as a function of travel time and distance using the following equation.

(1) 

Where *CV*, congestion variability, is the ratio of the standard deviation of travel time to average travel time; *CI*, a congestion index, is the ratio of average travel time to free-flow travel time; *D* is the road-segment distance, , and coefficients to be estimated empirically. is a constant, measures the effect of *CI* on *CV* and measures the effect of distance on *CV*.

The model uses a congestion index, *CI* as a key explanatory variable of variability, where *CI* is defined as the ratio of the mean travel time to the free flow travel time for a journey (though not for road links). This gives model-users a simple way of generating travel time variances from mean travel times. Reliability is then measured as the coefficient of variation (*CV* = ratio of standard deviation to mean). This standardises the magnitude of the deviation from the empirical observations to ensure that it is consistent across contexts.

Hyder Consulting, Black and Fearon (2008) estimated the following equation to predict congestion variability from day-to-day variation in traffic conditions and incidents, currently used in the UK Transport Guidelines:

(2) 

This formula can be applied to estimate changes in the standard deviation of travel times from transport projects in urban area. To do this, the equation can be rearranged to predict the standard deviation of journey time as a function of journey time and distance (by multiplying the equation with average travel times). The equation was estimated based on areas with average free flow speeds of 37 to 47 km/h. Using an average free flow speed of 44.5 km/h and expressing this as 0.01236 km per second, the change in journey time variability) resulting from a transport project is given, under the assumptions that distance and free flow speed do not change, by the following formula (DfT 2014)

(3)

where is the change in standard deviation of journey time from *i* to *j* (in seconds), and are the average journey times before and after the changes from *i* to *j* (in seconds) and is the journey distance from *i* to *j* (in km).

*3.2.2 Model specification: empirical study*

Based on the UK model presented above the following empirical model was estimated for key roads in Australia and New Zealand:

(4)

where is the standard deviation of travel time; is the average travel time; is the free-flow travel time; and is the distance. The i indexes the street and is an error term for statistical estimation. is a constant, measures the effect of CI on CV and measures the effect of distance on CV. The UK model is transformed by natural logarithms for purpose of estimation.

3.3 Results

This section presents the key results of this analysis. The estimated coefficients have the same interpretation as in the UK equation, and their use is explained further below.

The primary model was estimated using data from the entire sample, across all jurisdictions available in both Australia and New Zealand. Table 2 below presents the results of this pooled regression. The parameter value column reports the value that would be used in applying the regression results to the UK formula.

Table : Pooled regression results

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Coefficient** | | **Estimate** | **t-statistic** | Parameter Value |
|  | | -3.128\*\*\* | (-13.30) | 0.044 |
| (CI) | | 3.959\*\*\* | (10.41) | 3.959 |
| *(D meters*) | | -0.0328 | (-1.69) | -0.0328 |
| Sample size | | | 2702 | |
| R2 | 57.73% | | | |

Note: \*\*\* indicates a p-value of <0.01, highly significant. Standard errors are clustered at the jurisdiction level.

The coefficients on CI and distance are of the same sign as the UK model. However, the coefficient on distance is not significantly different from zero at the 5% level, and the coefficient on CI is substantially larger than that estimated for the UK.

A further set of regressions were estimated at the jurisdiction level, allowing both the CI and distance coefficients to vary across roads in each jurisdiction. The following Table 3 presents these estimates.

Table : Jurisdiction level regression results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Jurisdiction** | **CI** | **D (meters)** | **Constant** | **α** | **Sample size** | **R2** |
| Adelaide | 6.541 | -0.0408\* | -3.374 | 0.034 | 542 | 54% |
| Auckland | 2.974 | -0.0923 | -2.466 | 0.085 | 247 | 58% |
| Brisbane | 4.342 | 0.0108+ | -3.562 | 0.028 | 345 | 50% |
| Canberra | 4.793 | -0.00721+ | -3.434 | 0.032 | 118 | 58% |
| Darwin | 8.742 | -0.086+ | -3.52 | 0.030 | 120 | 30% |
| Hobart | 5.17 | -0.0499+ | -3.283 | 0.038 | 114 | 64% |
| Melbourne | 3.221 | -0.0318+ | -2.814 | 0.060 | 461 | 61% |
| Perth | 6.194 | -0.103 | -2.98 | 0.051 | 76 | 58% |
| Sydney | 2.466 | -0.0816 | -2.144 | 0.117 | 556 | 60% |
| Wellington | 5.477 | -0.0483+ | -3.587 | 0.028 | 123 | 59% |

Note: All variables significant at the 5 per cent level except where specified, \* indicates significant at the 10 per cent level, + indicates insignificance at standard levels. Robust standard errors reported. Alpha is calculated as exp(Constant).

All of the coefficients on CI were highly significant and of a large magnitude, as in the pooled regression above. Several distance coefficients were significant; however, the magnitude is not consistent across jurisdictions. Figure 3 below illustrates the relative magnitude of these coefficient estimates across jurisdictions. The CI estimate appears most consistent in magnitude across all jurisdictions, as does the constant term. Note that, in this figure, distance is scaled to be visible on the chart.

Figure : Jurisdiction level coefficient estimates



A further set of models were estimated, stratifying the data by approximate speed zone. This approach intends to allow the CI coefficient to vary across road type, as it may be that the relationship between average travel times and travel time variability differs systematically depending on road type.

Data on the exact speed zone of each road segment was not available. To stratify by speed zone, the 75th percentile of average speed was taken as approximately representative of the road type. The following Figure 5 presents coefficients from the estimated model. There appears to be an upward trend in the CI coefficient as the speed zone increases. This would indicate that travel time variability is more sensitive to average travel times on roads with higher speeds. As above, the coefficients on distance varied in magnitude and were not significant in any of the models.

Figure : Estimates stratified by speed 

Note: the coefficient on *CI* and the constant are highly significant; the coefficient on distance is not significant at the 5 per cent level in any equation. Standard errors clustered at the jurisdiction level.

4. Application in CBAs and road use forecasting

The following parameters set out in Table 4 can be used to estimate reliability changes from road projects.

Table 4: Recommended parameter values

|  |  |  |  |
| --- | --- | --- | --- |
| **Parameter** |  |  |  |
| Adelaide | 0.034 | 6.54 | -0.04 |
| Auckland | 0.085 | 2.97 | -0.09 |
| Brisbane | 0.028 | 4.34 | 0.01 |
| Canberra | 0.032 | 4.79 | -0.01 |
| Darwin | 0.030 | 8.74 | -0.09 |
| Hobart | 0.038 | 5.17 | -0.05 |
| Melbourne | 0.060 | 3.22 | -0.03 |
| Perth | 0.051 | 6.19 | -0.10 |
| Sydney | 0.117 | 2.47 | -0.08 |
| Wellington | 0.028 | 5.48 | -0.05 |
| **All cities** | **0.044** | **3.96** | **-0.03** |

These estimates can be applied using Formula 5:

(5)

Where is the difference between the standard deviation in travel time that could potentially be achieved by implementing a project (measured in minutes), *D* is the route distance (measured in meters), the free flow travel time and being the average travel time (measured in minutes).

The formula can be applied to estimate reliability benefits derived from projects located in urban areas. To do this, the following input data are required:

* Number of trips before and after an intervention;
* Average and free flow travel time before and after an intervention; and
* Distance.

4.1 Worked example

A worked example of how the estimated parameters can be used to estimate the impact of road improvements (e.g. investment in an additional lane) on travel time variability is presented in the remainder of this Section. In this example, the implementation of the road project represents the Project Case, while the Base Case represents a situation where no project is implemented (the business-as-usual scenario). The calculation of incremental reliability benefits under the Project Case compared to the Base Case includes three steps as described in the remainder of this Section:

* Step 1: Calculate the change in road users’ reliability under the Project Case compared to the Base Case (measured in minutes);
* Step 2: Multiply the change in reliability estimated under step 1 with the number of travellers benefitting from the improvement; and
* Step 3: Apply the value of travel time parameter value, adjusted by the reliability ratio, to monetise the change in reliability benefits calculated under step 2.

The road used in this example is a road segment of 1 km length. As an example, assume that a project potentially leads to a decrease in average travel times by 8 seconds with no change in free-flow time. Table 5 provides the key changes from implementing the project.

Table 5: Key statistics for intervention

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **Symbol** | **Base Case** | **Project Case** |
| Travel time (s) |  | 80 | 72 |
| Free flow time (s) | *ft* | 60 | 60 |
| Distance (m) | *D* | 1,000 | 1,000 |

The project potentially leads to the following reliability improvement. Note that this calculation uses the ‘All Cities’ parameter values.

(6)

Finally, to estimate the dollar value benefits associated with this reduction in travel time variability, the following equation can be applied. This formula estimates the daily reliability benefits that could be achieved by implementing the example project.

(7)

with RR being the ‘reliability ratio’, J being the number of journeys and VTTS the value of travel time savings. The reliability ratio is a measure of the importance that travellers place on time lost due to reliability concerns relative to travel time. Both, parameter values of the VTTS and the reliability ratio is commonly reported in project appraisal guidelines. This formulation uses a standard approach to calculating the reliability benefits, by multiplying the reliability ratio by the value of travel time savings (VTTS) thereby generating a value of reliability (VOR) measured in dollars per hour of travel time variability.

Finally, in the case where a transport project leads to an increase in road users it has been recommend that the rule of half is applied to calculate the reliability benefit for these new users.

In line with current practice, reliability benefits estimated based on the proposed formula should only be included in transport appraisals to test the sensitivity of the economic performance of a project (using the Benefit-Cost Ratio and Net Present Value). It should not be included in the core estimates. The reason for this is the limited availability of robust values of reliability (as discussed in Section 6 of this paper).

4.2 Guidance on application of formula

It should be noted that this approach is intended to be used as an additional set of parameter values which could be applied to the output from strategic transport models. That is, it can be applied to models that estimate changes to mean and free flow travel times to then estimate the benefits from changes in travel time reliability as part of a project appraisal. This is in contrast to an approach which would incorporate measures of reliability directly into existing strategic transport models (de Jong and Bliemer 2015).

The guidance included here is most appropriately applied to appraisals which rely on link based assessments of the impact of projects on average travel times and travel time reliability. This formula should not be applied to estimates for representative O-D journeys. Where appraisers utilise traffic models that include matrix estimation techniques to simulate car journeys, model based estimates of changes in the standard deviation of links (or total journeys) should be used, where they are available. These in-model estimates can then be converted to dollar value benefits through the application of a reliability ratio as described in the interim guidance provided here.

In the case where in-model estimates of standard deviations are not available, the estimates of mean and free flow travel times from traffic models which utilise matrix estimation techniques should be converted to a tractable number of link based results. The out-of-model formula presented in this guidance can then be applied to measure standard deviations. These standard deviations should then be converted to variance estimates, before being aggregated across links, noting that this step assumes zero aggregate spill-over effects of variability between links. This total variance estimate should then be converted to a total standard deviation measure, which can then be used to estimate the total dollar value benefits from the modelled intervention.

**5. Discussion and areas for further research**

The modelling approach used in this paper is based on an existing approach developed in the UK. This section provides a discussion of the statistical issues identified in modelling and areas for future research. Further study extending the techniques employed and specifying a model directly applicable to Australian roads is recommended.

5.1 Functional form

Examination of the underlying data and the model’s predictions suggests that the functional form used in the UK model performs well for most roads but does not perform well for roads with high variability (more extreme values of CI). This indicates a possible mis-specification of the functional form. As Figure 5 illustrates, the relationship between *CV* and CI appears to exhibit diminishing returns. That is, increases at a decreasing rate with respect to . This would indicate that the assumed functional form of the relationship between CV and CI in the UK model is poor for larger values of the *CI*.

Figure : Model prediction



Based on the chart above, an alternative functional form could be appropriate. As a comparison to the method used in the UK congestion model, a linear-log relationship is considered below. Following the notation introduced in Section 3.3.2, the form of the regression model is given by:

(8)

The interpretation of this model being that percentage changes in the independent variable are associated with unit changes in the CV ratio. The predicted values from this specification are presented in Figure 6.

Figure : Linear-log model prediction



The functional form appears more appropriate for the data gathered than that based on the UK congestion model, in particular for more extreme values of CI. However, this specification is preliminary and requires further statistical investigation. For example, further consideration of the distribution of the dependent variable is required. Under certain assumptions, the CV will come from a distribution in the gamma family. Variants of the gamma distribution are more appropriate for modelling right-skewed, non-negative data.

The poor performance of the UK congestion model for highly variable road links could be driven by a number of factors. A primary contributor may be that the sample used for the UK analysis incorporated road use journeys instead of a combination of road segments over time (as our data did). It may also be the case that the UK model does not appropriately take into consideration the diversity and condition of Australian roads. This is an important area for future research.

5.2 Treatment of Outliers

It was noted that, without considerably more detailed information, it is not possible to remove outliers on a systematic basis consistent with theory. Therefore, for this study, all observations were included.

As a test of robustness, outlier removal was performed and the models were re-estimated. The rules for the removal of observations were:

* Reject observations if the speed is greater than +/- 100% of average speed; and
* Reject observations if the travel time falls outside +/- 4 standard deviations from the mean.

Outlying observations were removed prior to aggregation up to a street level. Results from the model estimated on this restricted sample are presented in Figure 6.

Table : Regression results, outliers removed

|  |  |  |
| --- | --- | --- |
| **Coefficient** | **Estimate** | **t-statistic** |
|  | -3.419\*\*\* | (-19.20) |
| (CI) | 4.239\*\*\* | (11.21) |
| *(D meters*) | -0.022 | (-1.45) |
| Sample size | 2678 | |
| R2 | 59.97% | |

Note: \*\*\* indicates a p-value of <0.01, highly significant. Standard errors are clustered at the jurisdiction level.

The estimate of , the coefficient on CI, is approximately seven per cent larger after the removal of possibly outlying observations. Generally, however, the model’s implications remain consistent across the model estimates.

Future research could consider the effect of possible outlying observations on the estimated model’s coefficients, including a more systematic method for determining outliers (and considering the effect of other variables, such as weather and road conditions). In a broader sense, future work in modelling the relationship between travel time and congestions could take into account the breadth of available information on road segments throughout the year.

5.3 Origin-destination aggregation

Use of the estimated model to construct variance estimates based on a journey from origin to destination raises an important issue. A basic model assumption is that errors across streets (road segments) are independent. This is an issue for inference, and the standard errors have been adjusted to account for this possibility. However, in the absence of an explicit model of the spill-over effects that unexpected increases in variation in travel time will have on surrounding roads, the independence assumption is required to construct journey level estimates.

Further research could consider the application of techniques from spatial econometrics in order to estimate the spill-over effects of congestion across road segments. This would provide a more robust, albeit considerably more complicated, framework from which to construct journey level variance estimates.

**6. Conclusions**

This study estimates the relationship between average travel times, road segment distance and travel time reliability. To do this, the ‘UK model’ for travel time reliability (Hyder Consulting, Black and Fearon 2008) was re-estimated using data collected in Australia and New Zealand in 2015. The dataset contains observations on average travel times and standard deviations for 17,457 individual road segments within Australia and New Zealand cities. The results of the study show that the relationship is similar to the one found in the UK, but with differences in the magnitude of the effects of the variables.

The results from this study may be used to provide an interim update to guidelines for transport appraisals which seek to incorporate travel time reliability; in particular, for circumstances where only expected changes to average travel times are known.

Acknowledgements

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1. A “web service” is a system that accepts specially formatted messages over a network (for example, the Internet) and responds with data or information [↑](#footnote-ref-1)