Abstract

During the last few years, increasing attention has been paid to the problem of travel time variability caused by congestion on urban roads. Several countries have decided or are considering to include the cost of travel time variability in their cost-benefit analyses, including the UK, Holland and Sweden.

Travellers’ valuations of travel time variability has been investigated in several studies. However, studies that try to provide quantitative methods to forecast travel time variability (or rather, effects on variability of various investments or policy measures) are still rather scarce. The present study is an attempt to develop such a method.

Using data from Stockholm’s automatic camera system for travel time measurements, the relationship between congestion levels and travel time variability is investigated. We show that there is a stable and typical relationship between the relative standard deviation of travel time (standard deviation divided by travel time) and the relative increase in travel time (travel time divided by free-flow travel time). Using this, we estimate a function that can be used to predict how changes in congestion affect the standard deviation of travel time. This function has been used together with standard traffic assignment software (emme/2) to forecast the socioeconomic benefit of reduced travel time variation caused by a proposed road investment (the western bypass in Stockholm).
1 INTRODUCTION

As congestion problems are growing more severe in urban regions, the problem of unpredictable travel times is receiving increasing attention. In many cases, this problem is seen as worse than the increased travel time in itself. Investments in infrastructure, or other transport policies, are often motivated by the need to reduce unexpected delays and unreliable travel times.

Since travel time variability affects people’s utility and their travel behavior, it seems natural to try to include these phenomena in cost-benefit analyses (CBA). In fact, several countries consider doing this or have already. Holland has introduced “reliable travel times” as a goal for transport policy, and is well under way to introduce travel time variability in their CBA methodology (Kouwenhoven, 2005a; Hamer et al., 2005). In the UK, there is ongoing work to introduce travel time variability in all types of impact analysis, including CBA (Department for Transport, 2004).

Travellers’ valuation of travel time variability has been investigated in several studies (see e.g. Hamer et al., 2005, or Eliasson, 2004, for surveys). However, studies that try to provide quantitative methods to forecast travel time variability (or rather, effects on variability of various investments or policy measures) are still rather scarce. The present study is an attempt to develop such a method. The approach is essentially parallel to developing volume-delay functions; just as volume-delay functions describe the relationship between traffic volume, capacity and travel time on a link, our intention is to try to develop a function that describes the relationship between travel time, free-flow travel time and the standard deviation of travel time.

The study focuses exclusively on car trips in central urban areas. However, it is most likely that the phenomenon of travel time variability is relevant also in other settings – long-distance trips, public transit trips etc.

2 ABOUT TRAVEL TIME VARIABILITY

Travel time variability is the random, day-to-day variation of the travel time that arises in congested situations even if no special events (such as accidents) occur. If congestion is severe, this variation may be significant. The unreliability means that many travelers must use safety margins in order not to be late. In some cases, the margin will turn out to be insufficient, and the traveler will be late nevertheless. In the former case, an additional disutility (beyond that measured by pure mean travel time) arises since effective travel time can be said to be greater than actual mean travel time. In the latter case, the lateness will cause some sort of additional disutility. The social loss caused by the travel time variability is the sum of those two disutilities.

There are several factors causing travel time variability. Following Arup et al. (2004), these can be divided into one component due to "incidents", while what remains is referred to as "day-to-day variability" (DTDV). This in turn can be divided into two components: one due to unpredictable variations in demand, and the other due to random fluctuations in capacity:
travel time variability = DTDV + Incident-related variability

DTDV = Demand-related variability + Capacity-related variability

There are several ways to quantify travel time variability. We have chosen to use the standard deviation of travel time, because of two reasons. First, it worked better when estimating than various measures based on travel time percentiles that we tried (e.g. the difference between the mean and the 90-percentile or the difference between the 90- and the 10-percentile). Second, this is the most common measure in valuation studies. Typically, valuation studies assume a (reduced-form) utility function on the form

$$u = \alpha t + \beta c + H\sigma$$

where t is travel time, c travel cost and \(\sigma\) is the standard deviation of travel time (\(\alpha\), \(\beta\) and \(H\) are parameters to be estimated). This approach also makes it relatively straightforward to introduce variability into forecasting models and CBA methodology.

3 DATA

The data we will use are continuous measurements of travel times on several streets and roads in and around central Stockholm. Travel times are measured continuously through a camera system, where pictures of number plates are taken when vehicles enter and leave each link. The number plates are then matched together, and the travel time for each vehicle is calculated. Each period of 15 minutes, the median travel time on the link is calculated (after a filtering process to weed out various sorts of errors). The median is used rather than the average in order not to let vehicles stopping along the link (buses, shoppers) affect travel time measurements.

All the links can be characterised as “urban” roads, i.e. they are neither highways nor small, “local” streets. Typically, they have two lanes in each direction (sometimes only one), a speed limit of 50 km/h (although some have 70 km/h), with traffic volumes mostly between 15 000 and 50 000 vehicles per day (summing both directions) and quite a few (most often signalled) intersections. Lengths vary from 300 meters to 5 km.

We used data from 84 links, Monday-Thursday during the period September 1 – December 15 2005. Sometimes, we used a subset of 20 links that provided the most reliable travel time measurements (the system was still in a development stage at this time, and hence not all links provided reliable data each day). For each link, we calculated average travel time and the standard deviation of the travel time for each 15 minutes period – hence, each link produced 96 “measurements” of mean travel time and standard deviation (there are 96 quarters in 24 hours).

That we split the day into 15 minute-periods is an implicit assumption that this is the relevant “time resolution” that travelers base their decisions on. In general, the more coarse this “time resolution” is chosen, the larger will the calculated variability be (and vice versa). Our choice is essentially only motivated by intuition: it seems reasonable that most travellers will “know” the
variations in (expected) travel conditions on a 15-minutes basis. Investigating this further would certainly be worthwhile.

4 INVESTIGATING TRAVEL TIME VARIABILITY

Before we present estimation results, it is useful to get some “qualitative” feel for the standard deviation.

The diagrams below show mean travel time (red) and 10- and 90-percentiles for a few links. A striking feature is the large variation of travel time – the 10% “best” days, travel times are close to free flow even during rush hours, while the 10% “worst” days, travel times may be twice as long than average travel times (or more), and at least four times as long as the 10% “best” days.

![Figure 1. An example of travel times: Valhallavägen (two directions). Red is average travel time, black dotted lines are 10- and 90-percentiles of the travel time.](image)

The example below (showing the same link in two directions) shows that travel time variability does not have to be high even if congestion is. During afternoon rush hours on the right pane, the variability (the distance between the 10- and 90-percentiles) is very high, while it is fairly low during morning rush hours on the left pane.
Figure 2. Another example of travel times: the Central bridge (two directions). Red is average travel time, black dotted lines are 10- and 90-percentiles of the travel time.

From the figures above, it seems apparent that there is a relationship between congestion (i.e., travel time longer than the free-flow travel time) and travel time variability. In the figures below, the green line at the bottom shows the standard deviation. It is apparent that the standard deviation generally increases when congestion does.

Figure 3. Average travel time (red), 90-, 80-, 20- and 10-percentiles (black dots) and standard deviation (green). (The link shown is Valhallavägen in two directions.)

The left diagram below shows that standard deviation tends to increase (in absolute terms) when travel times are long. This is hardly surprising. More interesting is the right diagram below, which shows that the relative standard deviation (standard deviation divided by travel time) increases with congestion, measured as the relative increase in travel time (travel time divided by free-flow travel time minus 1).

Figure 4. Left: standard deviation vs. travel time. Right: relative standard deviation vs. relative increase in travel time (0 = free flow). Each dot is one 15 minute interval on a certain link.

It is also interesting to note that (relative) standard deviation decreases for very high congestion levels. This is expected theoretically: when a link is
hypercongested, the travel time will be virtually certain. (A nice simulation experiment showing this can be found in Nagel and Rasmussen, 1995.)

4.1 Is the distribution of travel times skewed?
An interesting question is whether the distribution of travel times is skewed. This answer to this has implications for how stated choice experiments are formulated, and may have also implications for whether the standard deviation is an appropriate measure to use for CBA.

An initial guess might be that the distribution of travel times might be “skewed to the right”, i.e. deviations “upwards” – longer travel times than the median – is more common and/or larger than deviations “downwards”. But it turns out that this intuition is not particularly correct. In fact, the distribution of travel times can best be described as “fairly” symmetric.

First, a visual inspection of the position of the percentiles show that they often look like the diagrams below. There, the percentiles are fairly symmetrically distributed from the median (the middle line). Moreover, the median lies close the mean, also indicating a symmetrical distribution.

![Diagrams showing percentiles](image)

**Figure 5.** Average travel time (red), 90-, 80, 50,- 20- and 10-percentiles (black).

However, examples as those below can also be found. There, the 90-percentile lies far above the other percentiles, and the mean travel time is well above the median, indicating a long tail to the right.
Turning from such anecdotical evidence to more formal measures, we investigate the skewness of the distributions. The skewness is defined as 
\[ S = \frac{E((X-m)^3)}{\sigma^3} \] (where \( m \) is the mean and \( \sigma \) the standard deviation). \( S = 0 \) means that the distribution is perfectly symmetric. \( S < 0 \) means that the distribution is skewed to the left, and vice versa.

The histogram below shows the skewnesses of all distributions. Since there are 92 links and 96 quarters, we get 8832 distributions.

The histogram shows that some distributions are skewed to the left, others are skewed to the right, but the majority is hardly skewed at all. However, there are more right-skewed than left-skewed distributions. In particular, there are a number of clearly right-skewed distributions, while there are no distributions with such a significant left-skewedness.

So, the majority of the distributions are not particularly skewed at all, but there are a few clearly right-skewed ones. But which are they – i.e. when does right-skewness occur? One might guess that it is when congestion gets severe, since incidents then will have more severe consequences. Further, one might guess that the distribution gets more skewed when standard deviation increases. Below, we show that there is something to this: the skewness (on
the y-axis) is somewhat higher for high congestion (left) and high standard deviation (right).

![Graph showing skewness against relative increase in travel time and standard deviation](image)

**Figure 7.** Skewness (y-axis) against relative increase in travel time (left) and standard deviation (right).

Linear regressions of the skewness on the relative increase in travel time and on the standard deviation, respectively, lend some support to this, but very little ($R^2 = 0.02$ and $R^2 = 0.12$, respectively).

## 5 ESTIMATION RESULTS

### 5.1 Choice of functional form

Above, we showed indications of a relationship between the relative standard deviation ($\sigma/t$, standard deviation divided by travel time) and the relative increase in travel time ($t/T$, travel time divided by free-flow travel time), which is a measure of congestion. For low congestion levels, $\sigma/t$ remains low, but then it starts increasing when $t/T$ approaches about 2. The diagrams below show $\sigma/t$ vs. $t/T$ for 20 different links, cutting the pictures at $t/T = 3.5$. 
Figure 8. $\sigma/t$ (standard deviation divided by travel time) vs. $t/T$ (travel time divided by free-flow travel time) for 20 links. Each dot is one 15-min. period. Diagrams have been cut off at $t/T = 3.5$

From these pictures, we see that we need a functional form that remains roughly constant for low “congestion” ($t/T$) levels, and then increases. Moreover, we need to guarantee that $\sigma/t$ will always be positive, since we use the function for forecasting, not just for inference.

But for high congestion levels, relative standard deviation ($\sigma/t$) starts to decrease. As mentioned, this is expected for theoretical reasons: when congestion is extremely high, travel time is virtually certain to approach some kind of “maximal” travel time. The diagrams below are the same as those above, except that we haven’t cut the x axis.
Hence, we need a function that will first remain constant, then rapidly increase, and then decrease again, always remaining positive. After trying quite a few expressions, the following turns out to work fine:

\[
\frac{\sigma}{t} = \exp\left(\alpha + \beta \left(\frac{t}{T} - 1\right) + \gamma \left(\frac{t}{T} - 1\right)^3\right)
\]

\(\alpha, \beta, \) and \(\gamma\) are parameters to be estimated. We let \(\alpha\) depend on the time-of-day \(\tau\), dividing the day into six periods: night, before morning peak, after morning peak, mid-day, before afternoon peak, after afternoon peak, evening. This is due to indications in an (unpublished) study by John Bates, where variability seemed to be lower during the “queue build-up” phase than during the “fade-out” phase. This was not confirmed, however, in the present study; we will return to this.

5.2 Estimation results

Estimating the function above\(^1\), we end up with the following parameters:

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\(^1\) We used the statistical software R for estimation – see www.r-project.org.
lm(formula = log(y) ~ (x + x3 + as.factor(tidpkt)))

Residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2.74777</td>
<td>-0.39431</td>
<td>0.05745</td>
<td>0.34576</td>
<td>2.46052</td>
</tr>
</tbody>
</table>

Coefficients:

|            | Estimate | Std. Error | t value | Pr(>|t|) |
|------------|----------|------------|---------|----------|
| (Intercept)| -2.505876| 0.033019   | -75.892 | < 2e-16  ***
| x          | 1.230062 | 0.038173   | 32.223  | < 2e-16  ***
| x3         | -0.036264| 0.001691   | -21.448 | < 2e-16  ***
| as.factor(tidpkt)1 | -0.418463| 0.061787 | -6.773  | 1.73e-11 ***
| as.factor(tidpkt)2 | -0.337678| 0.072867 | -4.634  | 3.85e-06 ***
| as.factor(tidpkt)3 | -0.663901| 0.046011 | -14.429 | < 2e-16  ***
| as.factor(tidpkt)4 | -0.484760| 0.072883 | -6.651  | 3.90e-11 ***
| as.factor(tidpkt)5 | -0.337188| 0.074103 | -4.550  | 5.73e-06 ***
| as.factor(tidpkt)6 | -0.490893| 0.044515 | -11.028 | < 2e-16  ***

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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5949 on 1717 degrees of freedom
Multiple R-Squared: 0.5044, Adjusted R-squared: 0.5021
F-statistic: 218.5 on 8 and 1717 DF, p-value: < 2.2e-16

Table 1. Estimation results. The variable x is (t/T-1), the variable y is σ/t. “tidpkt” means time-of-day – see below.

The definition of times-of-day used for the constant (the α variable) is shown below.

0. 20:00 – 6:15  (night)
1. 6:30 – 8:15  (before morning peak)
2. 8:30 – 9:45  (after morning peak)
3. 10:00 – 14:45 (mid-day)
4. 15:00 – 17:15 (before afternoon peak)
5. 17:30-18:45  (after afternoon peak)
6. 19:00 – 19:45  (evening)

Table 2. Definition of times-of-day.

We could not find any evidence for the hypothesis that variability was higher after the peak than before (during the “build-up” phase). However, variability was higher during night hours (index 0) and lower during mid-day. Other differences are not significant.

The model fit is decent but not very impressive, with R² = 0.50. We also tried excluding nighttime observations (τ=0, τ=6), but this did not change the estimated parameters significantly. R² increased somewhat, though, to R² = 0.56.

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Other explanatory variables that were tried included
- number of lanes
- number of intersections
- speed limit
- length
- volume-delay function (according to emme/2 coding)
- “type” of road (an indicator of its size and importance)

Neither of these contributed very much in terms of explanatory power. Besides, we were afraid to “over-fit” the model, since the number of links is fairly limited – especially considering that we wanted to use the results on an Emme/2 network with something around 15 000 links. Using the estimated function for forecasting, and not just for inference, makes the problem of over-fitting even more important to consider than it usually is. Since the network assignment procedure in Emme/2 does not take variability into account, strange things may happen in the CBA if other variables than travel time is used (that might happen anyway, but the risk is lower).

One reason not to include number of intersections and length is that it is difficult to introduce them into the function and still preserve the desirable property that the calculated variability remains unchanged if the link is split into several adjacent links.

One variable that is conspicuously absent is the traffic volume on the link. There are three reasons for this. First, we simply did not have observed data on this: the automatic travel time system only provide travel times, not traffic volumes. For some links, traffic volumes could have been obtained from other sources, however. Second, it should (in principle) not be necessary to introduce traffic volumes (or rather, traffic volume divided by the capacity of the link or something similar) since we already use the travel time and the free-flow travel time. This should – in principle – provide the “same” information, conceptually, that the traffic volume would. Third, and most important: since our intention is to use the estimated function together with a network assignment model (in our case Emme/2), we don’t want to introduce a possible inconsistency with the volume-delay functions of the network assignment model.
6 CASE STUDY: THE VALUE OF VARIABILITY REDUCTION

The western bypass is a planned major road investment in Stockholm. During the spring of 2006, Transek conducted the cost-benefit analysis of the bypass, and it was decided by the National Road Administration that travel time variability should be included into the CBA, as a test before a decision to include it in standard CBA.

The formula above was implemented as an Emme/2 macro, using travel times and free-flow travel times from the Emme/2 network as input. The diagram below shows the calculated relative standard deviation ($\sigma/t$) vs. relative increase in travel time ($t/T-1$) for the links in the network. Each dot corresponds to one link during morning peak.

![Figure 10. $\sigma/t$ vs. $t/T-1$. Observed (black) and predicted (red). Panes depict (from top left) arterials to/from the city centre, streets in the city centre, roads in the city centre and “ring roads” around the centre.](image)

![Figure 11. Calculated relative standard deviation ($\sigma/t$) for the links in the Emme/2 network, morning peak.](image)
Since this was only a test, and there was a pressing time limit, a few simplifications were made. First, all vehicles were assumed to have the same value of time. Second, only conditions during morning peak were considered, and this was then scaled to a value for the entire day. This consumer surplus of reduced variability $W$ was then calculated using rule-of-a-half:

$$W = \lambda \theta \sum_{ij} \frac{T_{ij}^0 + T_{ij}^1}{2}(\sigma_{ij}^1 - \sigma_{ij}^0)$$

where $T_{ij}$ is flow between the OD pair $(i,j)$, 0 and 1 refer to the situations with/without the investment, $\lambda$ is the value of time and $\theta$ is the scale factor from morning peak hour to the entire day.

Calculating $\sigma_{ij}$ for OD pair $(i,j)$, we assumed that standard deviations were independent across links. This is a strong assumption: arguments can be made both that they should be positively correlated and that they should be negatively correlated. Investigating this is one of the next steps in our research.

We arrived at the results shown below, using a valuation of variability where one minute standard deviation was worth 0.9 minutes of travel time, and a value of time that was 66 SEK/h. Two alternatives for the western bypass was considered, one a bit further to the west, and one closer to the city centre.

<table>
<thead>
<tr>
<th></th>
<th>Alt. 1 (west)</th>
<th>Alt. 2 (east)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer surplus</td>
<td>333</td>
<td>243</td>
</tr>
<tr>
<td>Budget effects</td>
<td>1764</td>
<td>1773</td>
</tr>
<tr>
<td>Travel time</td>
<td>20 973</td>
<td>21 677</td>
</tr>
<tr>
<td>Travel cost</td>
<td>1971</td>
<td>2480</td>
</tr>
<tr>
<td>Freight costs</td>
<td>1148</td>
<td>1257</td>
</tr>
<tr>
<td>Emissions</td>
<td>643</td>
<td>1612</td>
</tr>
<tr>
<td>Traffic safety</td>
<td>1018</td>
<td>1561</td>
</tr>
<tr>
<td>Investment costs (incl. marg. cost of public funds etc.)</td>
<td>-19570</td>
<td>-19570</td>
</tr>
<tr>
<td>Maintenance</td>
<td>-3232</td>
<td>-3031</td>
</tr>
<tr>
<td>Reduced travel time variability</td>
<td>2912</td>
<td>3420</td>
</tr>
<tr>
<td><strong>Total benefits excl. reduced variability</strong></td>
<td><strong>24 632</strong></td>
<td><strong>27 583</strong></td>
</tr>
<tr>
<td><strong>Total benefits incl. reduced variability</strong></td>
<td><strong>27 544</strong></td>
<td><strong>30 177</strong></td>
</tr>
<tr>
<td><strong>Net present value ratio incl. reduced variability</strong></td>
<td><strong>0.26</strong></td>
<td><strong>0.41</strong></td>
</tr>
<tr>
<td><strong>Net present value ratio incl. reduced variability</strong></td>
<td><strong>0.41</strong></td>
<td><strong>0.54</strong></td>
</tr>
</tbody>
</table>

Table 3. Costs and benefits of a western bypass, net present values.

What is interesting about this table in the present context is that the value of reduced travel time variability is quite significant – about 15% of the total value of travel time savings. Thus, it seems that it would be worthwhile to continue the work of including travel time variability into CBAs, at least in urban contexts.

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7 REFERENCES


Amelsfort (2005)


Bates (2003), presentation at the ETC.


Hollander (2005)


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