

## ITLS

## WORKING PAPER

## ITLS-WP-11-04

## Travel time expenditures and travel time budgets Preliminary findings

## By

Peter Stopher and Yun Zhang

February 2011

ISSN 1832-570X

## INSTITUTE of TRANSPORT and LOGISTICS STUDIES <br> The Australian Key Centre in <br> Transport and Logistics Management <br> The University of Sydney

## NUMBER:

TITLE:

ABSTRACT:

KEY WORDS:

## AUTHORS:

CONTACT:

## Travel time expenditures and travel time budgets Preliminary findings

There has been discussion now for four decades on the issue of whether or not people around the world have a constant traveltime budget. Most of the research into travel-time budgets has used large aggregate data sets and has shown that average amounts of time spent travelling are on the order of 1 to $1 \frac{1}{2}$ hours. There have also been a number of studies that have failed to find evidence of constancy in travel-time budgets. In this paper, the authors report on some preliminary research that uses data from a panel of 50 households that provided GPS data for a period of up to 28 days. In the research to date, the analysis deals only with evidence from one wave of the panel, to determine whether there is evidence over a period of one week of stability in travel-time expenditures. The data set provides very precise times of travel for each person for up to28 consecutive days of travel. The analysis looks at travel time expenditure on a daily basis per person and then aggregates this to a week. The issue of regression to the mean is also considered and reviewed and conclusions are drawn that it is not an issue in this analysis. Evidence is found of some stability in travel time expenditures, especially when data are averaged over a two-week period.

Travel time expenditure; travel time budget; transport; GPS
Peter Stopher and Yun Zhang

INSTITUTE of TRANSPORT and LOGISTICS STUDIES (C37)
The Australian Key Centre in Transport and Logistics Management
The University of Sydney NSW 2006 Australia
Telephone: +61 93510071
Facsimile: $\quad+6193510088$
E-mail: business.itlsinfo@sydney.edu.au
Internet: http://sydney.edu.au/business/itls

## 1. Background

For four decades the issue of whether or not people have a constant travel-time budget has been discussed. There have been many proponents of this concept, especially (Szalai, 1972; Zahavi ,1973; Zahavi, 1974; Zahavi and Ryan, 1980; Zahavi and Talvitie, 1980; Schaefer and Victor, 1997; Schaefer, 2000). Most of the research into travel-time budgets has used large aggregate data sets and has shown that average travel time expenditures are about 1 to $11 / 2$ hours (Downs, 2004). There have also been a number of studies that have failed to find evidence of constancy in travel-time budgets, e.g., Kitamura et. al.(1992), Purvis (1994), Levinson and Kumar (1995) and Levinson and Wu (2005) among others. Analysis of the US Nationwide Household Travel Surveys between 1983 and 2001 suggested that, if stable travel time budgets exist, then traveltime budgets in the US might be increasing by about 2 minutes per person per year (Toole-Holt et al., 2005). This latter finding does not, however, run in the face of Zahavi’s original work, since Zahavi (1974) also postulated that while travel-time budgets may be more or less constant, they would change over time.

The policy significance of a travel time budget is enormous. If people have a stable daily travel time budget, that time saved in one trip would be applied to other or additional travel (Zahavi, 1974). Similarly, other policies, such as Voluntary Travel Behaviour Change (Marinelli and Roth, 2002; Taylor and Ampt, 2003), which may lead to time savings over a day, are also likely to result in increased travel for other purposes elsewhere during the day or the week, so that the individual still tends to expend close to their travel time budget. Conversely, additional time spent on travel, e.g., as a result of increasing congestion, would be drawn from and would reduce the time spent in other travel. As pointed out by van Wee et al.(2002), the existence of stable travel time budgets suggests that no change total travel volumes will result from technological changes, economic growth, or transport policies. Travel patterns may change, but the overall amount of travel will not. Indeed, as population continues to grow, the total volume of travel will likely grow proportionately, irrespective of other influences. If stable travel time budgets exist, transport policies and investments will be more likely to shift travel both spatially and temporally, with some shifts taking place between weekdays and weekend days, and others within the same day.

### 1.1 Budget versus expenditures

A potential difficulty with the notion of travel time and travel cost budgets is how to observe a budget. One can fairly readily observe what a person actually expends. However, whether this expenditure is greater or less than the desired budget is not easy to determine. Previous empirical work on travel time budgets has, in fact, fallen into the trap of equating observed expenditure with budget. In this respect, those who have analysed travel time budgets using highly aggregate data from various metropolitan areas around the world have probably been more or less correct in the conclusions they have drawn, while those who have undertaken more disaggregate analysis of travel time expenditures, but mislabelled them as budgets are more clearly in error.

Assuming that people have travel time budgets and that the size of the travel time budget varies within the population, then because a travel time budget is probably less critical than a financial budget, it is reasonable to suppose that a person may exceed their budget on some days, while compensating on other days by expending less travel time, so as to average out to somewhere close to their actual travel time budget. This would mean that highly aggregate analysis of travel time expenditures would be likely to produce more or less an estimate of the average travel time budget of people, because, in a snapshot of data, there should be a reasonably symmetrical distribution of people exceeding their budgets and people expending significantly below their budgets. Overall, however, the central tendency of the data should be towards expenditure equalling budget and aggregate statistics should show this.

### 1.2 Regression to the mean

One issue that must be addressed before analysing the data is that of regression to the mean. In general, regression to the mean states that, if a first observation of some phenomenon tends to take an extreme value, subsequent measurements will tend to be less extreme and therefore closer to the mean (Galton, 1986; Weisstein, 1999). However, for regression to the mean to hold true, the underlying attribute must be largely the result of random events. Thus, if one were to draw a random sample from a population and measure some attribute of the members of the sample, the running average computed after each new sample member was measured would be expected to move closer to the mean. If this were not so, then sample surveys would be open to question and the science of surveys, which depends on the fact that increasing the sample size improves the accuracy of estimates of the population values, would fail.

The relevant question here concerns observations of the amount of time spent in travelling by one individual, measured repeatedly over a number of consecutive days. If these measurements of time spent travelling are found to fall closer to the mean as the length of time of observation is increased, is this a case of regression to the mean? We would suggest that it is not, because the time spent travelling each day by an individual is not a random event on each day, although it may be subject to random perturbations. Rather, to assume that such a finding is simply a statistical construct of regression to the mean is actually to apply the regression fallacy to the observations (Weisstein, 1999). Possibly, the past analyses of highly aggregate data regarding travel-time budgets are examples of regression to the mean, because, if the travel times of a large number of individuals are averaged from random samples, these averages will tend towards some overall mean as a result of the independence of the sample measures and the tendency of regression to the mean. However, if disaggregate data are used to measure time spent travelling and these measurements are repeated over a period of time, then a different conclusion arises.

In the case of repeated measurements of an individual over time, the successive observations of travel time are not a result of random events. Rather, if travel-time budgets exist and an individual, on the first day of observation, spent much more time on travel than their budget, then this individual would attempt, on the next day, to reduce the amount of time spent on travel. If this was again unsuccessful, then on the next and subsequent days, the individual would continue to attempt to make reductions in the amount of time spent travelling. If, on the other hand, the first observation of time spent travelling was well below the individual's budget, then it could be expected that much larger amounts of time might be spent on subsequent days, as the individual attempted to draw closer to his or her budget.

Therefore, the conclusion to be drawn is that a tendency of time spent travelling over a number of days for a specific individual to draw closer to a mean value is a behavioural construct and not a statistical construct. This also means that the present research on travel time budgets, which is, for the first time, based on multi-day and time-series data, is more likely to be able to substantiate whether or not a travel time budget actually does exist.

## 2. Description of the data

Over the past four years, ITLS has collected data from households using Global Positioning System (GPS) devices, providing detailed and precise measurement of travel and activities. These data offer a new opportunity to explore the concept of a travel-time budget by looking at travel-time expenditures over a period of a week or longer, and determining if there is evidence of a constant travel time budget. Given the previous discussion in this paper, the potential is that multi-day and multi-period data will show what one-day data cannot show. Indeed, one would look for evidence that mean travel time expenditures become progressively more stable as additional days of data are examined.

This paper reports on preliminary research that uses data from a panel of 50 households that provided GPS data for a period of 28 days. In the research to date, the analysis deals only with
evidence from one wave of the panel, to determine whether there is evidence over a period of one week, or more than one week, of stability in travel-time expenditures. While this is a small data set, it provides data on very precise times of travel for 79 persons for up to 28 consecutive days of travel. In fact, 60 individuals provided data on an average of 6 or more days per week for an entire 28-day period. The analysis looks at travel time expenditure on a daily basis per person and then aggregates this to a week and estimates the weekly average by person for weeks $1,2,3$, and 4 , and also combines weeks to determine if greater stability appears as the time period becomes longer, as would be expected.

One of the problems with the analysis of GPS data, however, is that there exists some doubt as to when sampled respondents did or did not travel at all. The GPS data will have certain days on which no travel is recorded. However, it is uncertain whether such days of no travel data are a result of the person not travelling anywhere on that day, of the device not being charged that day, or of the person forgetting to take the device with them. In subsequent data collection, ITLS has devised a short 'GPS Status' form on which people are asked to fill out what happened on each day of the survey with respect to the GPS device. For example, they can indicate that the device was carried all day, that the device appeared to run out of power by a certain time in the day, that the device was not carried for all or part of the day, or that the person did not travel that day. There is, of course, no validation check on such data. It is necessary to take the word of the respondent as being the best measure of truth.

The next section of this paper reports on analysis of the results of this status card from both 7day and 15-day data collection and suggests ways to apply these results to a 28 -day survey. Conclusions are also drawn as to the validity of what people report on these forms. Second, using the analysis results from the GPS Status form, the evidence for travel time budgets from the 28-day data set is examined.

### 2.1 Analysis of the GPS status form

There are four sets of data available for analysing the responses to the GPS Status form: two waves for a panel of about 45 households who carried devices for 15 days, and two waves for a panel of about 160 households who carried devices for 7 days. Results from these four panel waves are summarised in Table 1.

| Status | Wave 2 (7-day) | Wave 3 (7- <br> day) | Wave 3 (15- <br> day) | Wave 4 (15- <br> day) |
| :--- | :---: | :---: | :---: | :---: |
| Percent Stayed Home | 9.8 | 9.2 | 10.9 | 11.2 |
| Percent Forgot Device | 6.3 | 3.5 | 6.6 | 2.4 |
| Percent Took Device for Part Day <br> Percent Took Device for Whole Day | 11.8 | 13.4 | 16.1 | 14.4 |
| Number Person Days Reporting <br> Status | 72.0 | 73.9 | 66.5 | 72.0 |
| Number Missing | 3718 | 2055 | 791 | 250 |
| Total Sample Person Days | $1392(27.2 \%)$ | $241(10.5 \%)$ | $499(38.7 \%)$ | $185(42.5 \%)$ |

Table 1: Results of GPS status form for four panel waves

The percentages in the first four rows of Table 1 relate to those completing the status form and line 5 shows that about 27 percent of respondents failed to complete the status form for the 7 day survey, whilst this increased to around 40 percent for the 15-day survey. Apart from this difference in response rate, the percentages for each status are remarkably similar between the four panel waves. They suggest that about 10 to 12 percent of people stayed home all day on any particular day, that around 6 percent (remarkably dropping to just over 2 percent for Wave 4 15-day data) forgot to take the device on a particular day, and that about 13 percent took the device for part of the day. On average, about 70 percent of respondents who completed the form claimed to have taken the device for the entire day. Other research has suggested that average
non-mobility should be in the range of $8-15$ percent (Madre et al., 2003), or 11.8 percent in a specific case (Stopher et al., 2008). From this, the results in Table 1 appear to be reasonable and suggest that about 9-11 percent of days are genuine non-mobile days, while forgetting to take the device averages around 5 percent, and about 13 percent of days will have incomplete data.
From the above, it could be expected that about 15 percent of possible travel days should be missing, with approximately one-third of these being days when the respondent left the device at home and two-thirds being genuine no travel days. However, a more in-depth analysis of the data shows that the completion of the status card does not always correspond with what was measured by the GPS device. This is shown from the Wave 3 panel and Wave 4 Add-on (conducted at the same time and same location) in Table 2. For both days of no travel and days when the GPS was left at home, there are cases where the GPS shows travel on those days. On the other hand, there are a number of instances where the respondent reported taking the device for part or all of the day, but the GPS reported no travel. It seems quite plausible to assume that, when a respondent indicated either that they had taken the device with them all day or that they had taken it with them for part of the day, and no trips were recorded on the device, in fact this should have been reported as a day of no travel. If a respondent filled out the status card at the end of the week, the respondent may recall that he or she took the device with them whenever she or he went out, but does not remember correctly whether or not he or she went out each day.

| Number of <br> Trips | Stayed <br> Home All <br> Day | Left Device <br> at Home | Took Device <br> for Part of <br> Day | Took <br> Device for <br> Entire Day | Missing | Total |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 189 | 64 | 50 | 129 | 137 |  |
| $1-5$ | 20 | 11 | 192 | 978 | 196 | 1399 |
| $6-10$ | 7 | 3 | 61 | 484 | 74 | 629 |
| $11-15$ | 2 | 0 | 5 | 86 | 15 | 108 |
| $16-20$ | 0 | 0 | 2 | 20 | 3 | 25 |
| 21 and over | 0 | 0 | 1 | 1 | 1 | 3 |
| Total | 218 | 78 | 311 | 1698 | 426 | 2731 |

Table 2: Number of trips recorded by GPS versus device status report

A chi-square test comparing the overall distribution of numbers of trips by day to the same distribution for Add-on Wave 2, for which the status card was not used, showed no significant difference in the distributions. These distributions are shown in Figure 1. Based on the lack of significant difference, the status card results from Main Wave 3 (plus add-on wave 4) can be assumed to be applicable to Add-on Wave 2 data, to determine the proportion of days with no travel recorded that might be genuine no travel days and the proportion that represent such things as forgetting to take the GPS device. Two other distributions of interest are the distribution of the numbers of trips for those with status card missing versus the overall distribution for Wave 3 (plus add-on Wave 4) and the distribution of those with status card missing and the Add-on Wave 2 respondents. Again, neither of these distributions was significantly different from the one against which it was compared.
These results suggest two possibilities. First, the lack of a significant difference between the status card missing and the overall distribution for the augmented wave 3 data suggests that the data from this group can be assumed to be similar to those who completed the status card. This is helpful, because it allows an adjustment to be made on the zero trip counts among the different device status codes. Looking at the first four columns of Table 2, this suggests that the 137 respondent days with no trips and with the status code missing could be apportioned according to the distribution across the four status codes. Assuming that only status 1 and 4 represent genuine no travel days, then it could be assumed that 73.6 percent of the 137 trips with missing status are genuine no travel days. Adding those 101 trips to the 189 with status 1 and

129 with status 4 leads to the assumption that 419 of the 569 days with no travel recorded represent genuine no travel days.


Figure 1: Comparison of add-on wave 2 and main wave 3 distributions of numbers of trips
Second, this also suggests that, for Add-on Wave 2, the same proportion of no travel days can be assumed to be applicable to the number of person days with no travel. Thus, of the 676 person days with no trips appearing, it can be assumed that 497 represent genuine no travel days and should be factored into the averages of travel time per day, whilst the remaining 179 person days with no travel recorded must be assumed to be missing data. This is helpful for aggregate analysis of Add-on Wave 2 data but requires further assumptions to be made for any disaggregate analysis. In the latter case, it will be necessary to assume that specific days of no travel within each person's record are either genuine or not. This presents a rather more 'heroic' assumption than the aggregate assumptions and suggests a further refinement. The augmented Wave 3 data were examined in more detail to determine the frequency with which non-genuine no travel days arose in relation to the total number of no travel days by person. In other words, this amounts to the assumption that people tend either to take their GPS devices with them most or all of the time, or that they are sloppy about the survey task and may forget to take their device more often.

After extensive analysis of the no travel days and the device status from Wave 3, assumptions were made for the Add-on Wave 2 data. It was not reasonably possible to separate those days for which GPS data were obtained into partial and complete days. Hence, status 3 was assumed not to occur in the Add-on Wave 2 data; it was assumed that, if the device was left at home part of the day, it was left at home for the entire day, so code 2 would be appropriate. Therefore, if GPS data were present in Add-on Wave 2, a simulated code of 4 was assigned to each day. It was then necessary to divide those days for which no trips were recorded between code 1 and code 2. This is important because code 1 would count as a valid day of no travel, whereas code 2 would be interpreted as a missing value for travel and would have to be omitted from the calculation of travel-time expenditures.

Several analyses were undertaken and attempts were made to develop some type of a model to assign the status code, but the modelling effort was not successful. In the end, the decision that was made was to use a series of steps to assign the appropriate device code. From an analysis of Wave 3, it was found that people were much more likely not to travel all day on Sundays, followed by Saturdays and then Mondays.

An examination of the data also showed that it was more likely that a single day of no travel in the data was a day on which the person had not gone out all day, whereas when there were several consecutive days of apparent no travel, this was more likely to be a case of forgetting to take the device along. Therefore, a combination of steps were taken in which the status was more likely to be 1 on Saturday, Sunday, and Monday, and was more likely to be 2 if there was a block of days of no travel, or if the days were in the middle of the week. This process resulted in 457 of the 676 no travel days being assigned a code of 1, for a genuine no travel day, and 219 being assigned a code of 2 , indicating that the data were simply missing. These numbers provide a slightly higher proportion of missing data than the Wave 3 data suggested, which was felt to be appropriate, given that Add-on Wave 2 involved a 28 -day GPS task, which is considerably longer than the 7 and 15 days in Wave 3.

### 2.2 Analysis of travel time expenditures and budgets

Analysing the data from Add-on Wave 2, which provides about 28 days of GPS data for each of 72 individuals, it is possible to examine the evidence that may be available for travel time budgets. Overall, aggregating the GPS data to each person day, the mean time spent travelling by these 72 persons is 53.6 minutes per day, which is a bit lower than the supposed average of about 60 to 75 minutes, but is certainly within the expectations from prior work on travel time budgets and expenditure. This value, however, is very much subject to assumptions about genuine and non-genuine travel days. If a larger proportion of days for which no travel was recorded are assumed to be a result of not taking the GPS device, then this value would increase. At the person level, the lowest average amount of travel time spent on a day is 13.91 minutes, and the largest average amount of time spent is 137.3 minutes. The standard deviation of the average time per person is 27.26 minutes, which is quite small.

Because most prior work on travel-time budgets has concerned weekday travel only, Figures 2 and 3, exclude weekend days. In Figure 2, each category represents a 10 -minute interval, with category 1 being travel times from 0 to 19.99 minutes, up to category 14 which is 140 to 149.99 minutes. It is rather clear that the mode of this distribution is for category 3 ( 30 to 39.99 minutes). The median is 40 to 49.99 minutes. The overall average time spent travelling per day is 60.8 minutes.

Figure 3 shows the distribution of daily travel time expenditures for this sample. The results are, as expected, quite different from the mean plot shown in Figure 2. The mean is very close to the division between category 4 and category 5 . The mean value is over 60 minutes and is determined from just those days on which travel took place (the no-travel days were omitted from this graph to allow the scale to be of reasonable size, since there are over 400 no travel days). The travel times have been grouped identically to the previous exercise, except that there are now 16 categories, because individual days of travel include values up to over 700 minutes. Therefore, category 13 in this case is 130-149.99 minutes, category 14 is 150-199.99 minutes, category 15 is 200 to 499.99 minutes and category 16 is 500 minutes and over.


Figure 2: Distribution of average daily time expenditures for weekdays only
These two figures show that the averaging of travel times over the four weeks of observation tends to produce a distribution that would be consistent with an approximate budget, whereas the distributions of the individual daily travel expenditures gives very little clue to the budget. However, to pursue this notion further, it is appropriate to see what happens if the data are averaged by week or by two-week period, to investigate whether averaging over some period of time reflects a budget rather than the individual expenditures, and to get an idea of the time period for which averaging needs to occur to reflect the budget. This notion of averaging to produce a budget is based on the idea that, if an individual has a real fixed budget, then on a day-to-day basis, the individual may sometimes overspend and sometimes underspend their budget. However, if the budget is real, then over some period of time, the actual expenditures should average out to the budget, or to some percentage under the budget if the individual is in a situation in which it is possible to achieve their desired activities without expending all of the budget. For this investigation, and in keeping with prior work that has been based on weekday travel, weekend days are excluded from the analysis. There is also some potential that the weekends may be more variable, because of the discretionary nature of most weekend travel, so that inclusion of weekend days may make it more difficult to reach a stable average within the four weeks of data available.


Figure 3: Distribution of daily travel time expenditures for 1,045 weekday travel days
The mean travel times by week were plotted for the 72 individuals in the data set. It was apparent from the plots that there is still some marked variability from week to week in the travel time expenditures. However, there is also a clear indication that, for many respondents, the average amount of time spent daily on weekday travel already appears fairly constant. It is also interesting to note that the weekly averages are generally approaching somewhere around 60 minutes or so.

In the next step of the analysis, averages were obtained for successive two-week periods, i.e., for weeks 1 and 2 , weeks 2 and 3 , and weeks 3 and 4 . The results in terms of the daily average travel time on weekdays for the 72 respondents are shown in Figures 4, 5, and 6.
Figures 4 through 6 show much more consistency from fortnight to fortnight in the daily averages of travel time expenditures, suggesting that two weeks may be a sufficient length of time to obtain relatively stable estimates of average daily travel time expenditures, which may, in turn, approximate a travel time budget for most people. There are probably no more than about eight or ten individuals who show a marked variation in the average travel times, which represents about 10 percent of the data. In other words, for about 90 percent of respondents, a two week average of daily weekday travel time seems to stabilise over the period of observation for this data set. For this grouping of data, the average daily travel time is about 57.5 minutes. The standard deviation of the mean is about 33.3 minutes. As can be seen from Figures 4 through 6, there are a few individuals who average a travel time expenditure of over 100 minutes, while there are also a few who average less than 20 minutes.


Figure 4: Average daily travel time expenditure averaged over two weeks (first third of data)


Figure 5: Average daily travel time expenditure averaged over two weeks (second third of data)


Figure 6: Average daily travel time expenditure averaged over two weeks (last third of data)

## 3. Conclusion

While the analysis reported in this paper is rather preliminary in nature, it does suggest some initial conclusions and suggests some directions for further research. Among the conclusions of this research, the concept of a constant travel time budget appears to be well worth exploring further, especially using the more precise data available from GPS measurement. Certainly, the aggregation of the GPS data continues to provide evidence of an overall average of daily travel time expenditure of somewhere close to one hour per day. Second, the analysis reported here also suggests that one week of data may not be sufficient to estimate an individual's travel time budget, but that two weeks of data may be sufficient in most cases. There is still evidence that even a two-week average will, in about 10 percent of cases, provide a misleading value of the average daily travel time expenditure. Third, the analysis suggests that averaging daily travel time expenditures over two or more weeks may be a feasible way of measuring an apparent travel-time budget.

In terms of further work, the first and clearest issue to emerge from this analysis is that, with GPS measurement, it is critical to determine on which days respondents do not leave home, and on which days they leave home but forget to take the GPS device with them. Without more accurate data on which days for which no travel is recorded by the GPS are genuine no-travel days, an accurate average travel time expenditure cannot be determined. As a result of the analyses performed for this research, the need to redesign the form that asks people to report the status of their use of a GPS device on each day of the survey has already surfaced. Second, it would be useful to explore larger data sets than the one used in this research and then to include analysis of the demographics of the respondents to determine differences, for example, between workers and those not employed, as well as other categories, such as gender and life cycle. For this research, the data set was too small to permit such analysis to be undertaken with any statistical confidence. Third, it may also be useful to look at averaging over three weeks, to see the extent to which this may introduce further stability in estimates.

## 4. References

Downs, A. (2004). Still Stuck in Traffic, Brookings Institution Press, Washington, DC.
Friedman, M. (1992). "Do Old Fallacies Ever Die?" J. Of Economic Literature, Vol. 30, No. 4, pp 2129-2132.
Galton, F. (1886). "Regression Towards Mediocrity in Hereditary Stature", J. Anthropological Institute, Vol. 15, pp. 246-263.

Kitamura, R., J. Robinson, T.F. Golob, M. Bradley, J. Leonard, and T. Van der Hoorn (1992). A Comparative Analysis of Time Use Data in the Netherlands and California, Research Report UCD-ITS-RR-92-9, Institute of Transportation Studies, University of California, Davis.

Levinson, D. And A. Kumar (1995). 'Activity, Travel, and the Allocation of Time’, J. Of the American Planning Association, Autumn, pp. 458-470.

Levinson, D. And Y. Wu (2005). ‘The Rational Locator Reexamined: Are Travel Times Still Stable?’ Paper presented to the 84th Annual Meeting of the Transportation Research Board, Washington, DC (January).
Madre, J-l., K.W. Axhausen and M.-O. Gascon (2003). "Immobility: A microdata analysis." Paper presented at 10th International Conference on Travel Behaviour Research, Arbeitsbericht Verkehrs- und Raumplanung, 166, Lucerne, August.

Marinelli, P. A. and M.T. Roth (2002). TravelSmart Suburbs Brisbane-a successful pilot of voluntary travel behaviour change technique. Paper presented at the 25th Australasian Transport Research Forum, Canberra, Australia. October, 2002.

Purvis, C. (1994). 'Changes in Regional Travel Characteristics and Travel Time Expenditures in the San Francisco Bay Area’, Transportation Research Record No. 1466, pp. 99-109.
Schaefer, A. (2000). 'Regularities in Travel Demand: An International Perspective', J. Transportation Statistics, Vol. 3, No. 3, pp 1-31.

Schaefer, A., and V.G. Victor (1997). 'The Past and Future of Global Mobility', Scientific American, Vol. 227, No. 4, pp. 36-39.

Stopher, P.R., R. Alsnih, C.G. Wilmot, C. Stecher, J. Pratt, J. Zmud, W. Mix, M. Freedman, K. Axhausen, M. Lee-Gosselin, A.E. Pisarski, and W. Brög (2008). Standardized Procedures for Personal Travel Surveys, Technical Appendix to NCHRP Report 571, NCHRP Web-Only Document 93, (http://trb.org/news/blurb_detail.asp?id8858 ), National Academies of Sciences and Engineering, Transportation Research Board, Washington, DC.

Szalai, A. (1972). The Use of Time: Daily Activities of Urban and Suburban Populations in Twelve Countries, Mouton Publications, The Hague.

Taylor, M. and E. Ampt (2003). 'Travelling Smarter Down Under: Policies for Voluntary Travel Behaviour Change in Australia', Transport Policy, 10 (3), pp 265-177.

Toole-Holt, L., S.E. Polzin, and R.M. Pendyala (2005). ‘Two Minutes Per Person Per Day each Year: An Exploration of the Growth in Travel Time Expenditures’, Transportation Research Record No. 1917, pp. 45-53.

Wee, B. van, P. Rietveld, and H. Meurs (2002). ‘A Constant Travel Time Budget? In Search For an Increase in Average Travel Time’, Research Memorandum 2002-31, Vrije University, Amsterdam.

Weisstein, E. W. (1999). "Reversion to the Mean." From MathWorld--A Wolfram Web Resource. http://mathworld.wolfram.com/ReversiontotheMean.html

Zahavi, Y. (1973). 'The TT-Relationship: A Unified Approach to Transportation Planning', Traffic Engineering and Control, pp. 205-212.

Zahavi, Y. (1974). The 'UMOT' Project, Report prepared for the US Department of Transportation and the Ministry of Transport of the Federal Republic of Germany.

Zahavi, Y. and J.M. Ryan (1980). 'Stability of Travel Components over Time’, Transportation Research Record No. 750, pp. 19-26.
Zahavi, Y. and A.P. Talvitie (1980). 'Regularities in Travel Time and Money Expenditures', Transportation Research Record No. 750, pp. 13-19.

