

Variability in Day-to-Day Travel – Analysis of a 28-day GPS Survey

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1 Introduction

As part of a pilot test of the use of GPS as a tool for evaluating Voluntary Travel Behaviour Change (VTBC) strategies, ITLS set up a panel of approximately 50 households. Persons in the panel households who were over 14 years old have been asked to carry GPS devices with them for a period of 28 days. At this time, two waves of the panel have been conducted, although analysis has only been performed on the data of one wave, which is the subject of this paper. While the principal interests for the pilot survey relate to the use of the GPS panels as an evaluation tool, this paper concentrates on looking at what we can learn about the variability in day-to-day travel.

One of the problems uncovered in this pilot test was that not many of the people who were asked to take GPS devices for 28 days actually complied fully with the task. However, one of the problems with a multi-day GPS survey is that there is no ready way to distinguish between days when an individual genuinely did not travel anywhere, and days when the individual did not have an operating GPS device with them. Several reasons can result in not having an operating GPS device on a given day. Because the charge on a GPS device only lasts for 8 to 12 hours, the person may have forgotten or been unable to recharge the device to use on the next day of travel. Sometimes, people simply forget to take the device with them, while at other times they may make a conscious decision not to take the device with them, possibly because they feel it is inappropriate to be carrying the device for a particular trip, or because they are concerned about their privacy. Distinguishing among these situations is not possible without having respondents complete some type of questionnaire on this at the time of using the devices – an added burden. To deal with this, we developed rules, based on work status, numbers of consecutive days of no travel, and repetitive patterns to determine which were probably legitimate no travel days, and which were probably days of intentional or unintentional omitted travel. We describe these rules in a later section of this paper.

Traditional methods of travel surveys usually obtain only one or two days of travel from respondents. As is discussed elsewhere (e.g., Stopher *et al.*, 2006a), there is usually a drop off in reporting of travel on the second and subsequent days as respondents become fatigued and find the diary task too burdensome. Therefore, even when two or more days of data are collected in a traditional survey, it is often the case that the data for the second and subsequent days are compromised by drop off in reporting. Stopher *et al.* (2006a) found that there was a much higher rate of reported non-mobility on the second day, while other researchers have found that the trip rates in an interview survey tend to be lower on a second and subsequent day. For example, Golob and Meurs (1986) studied the Dutch mobility panel which asked respondents to report travel for seven consecutive days and found that there were statistically significant drops in reporting of travel over the seven-day diary period. It has been observed that repetitive trips, such as the journey to and from work or school, continue to be reported well on subsequent days. However, other trips, especially walking trips and other short trips, are frequently missing from subsequent travel days. In our work in New South Wales, we not only found a substantial increase in the reporting of no travel days on the second diary day in a self-administered postal survey, but also found a drop off in the trip rate, amounting to about 1.6 trips per household per day or about 0.61 trips per person per day. The Adelaide Household Travel Survey, which used a two-day diary, also experienced both effects. The non-mobility rate increased from 13.4 percent to 15.4 percent for persons and from 8.5

percent to 10.3 percent for households. At the same time, the trip rate dropped per person from 3.54 to 3.34 trips per person per day (Stopher *et al.*, 2006a).

A drop off in reporting is not likely to occur in a GPS survey. People who generally comply with the requested task will continue to take the GPS device with them throughout the period, and a drop off in recorded travel within any given day is highly unlikely, except as a result of unusual travel that may result in a loss of power for the GPS device after some number of hours of travel and other activity. Hence, the GPS records provide a far more reliable method to investigate daily variability in trip making and other time-dependent issues.

We first describe some basics of the data set obtained from the first wave of the 28-day GPS panel survey. After detailing our approach to identifying genuine no travel days from the days on which data are missing, we provide a number of analyses of variability in trip making over the period. Most of our analysis relates to a period of either 15 or 21 days, because we found that few respondents were diligent about using the GPS device for the full 28 days, whereas the sample sizes increased substantially when we cut the period back to either 21 or 15 days. We also look at some interesting comparisons between the first, second and third weeks of data recording.

2 The Data

As noted in the introduction, our sample consists of nominally 50 households, in which all members over the age of 14 years were asked to take a GPS device and carry it with them wherever they went for a period of 28 days. Respondents also completed a short household and vehicle survey form, and provided some data on themselves, personally. Instructions were provided for using the GPS device, and each device was equipped with a charger. The devices are described elsewhere (Stopher *et al.*, 2005), but are briefly about the size and weight of a mobile telephone, and can be carried in a bag, in a pocket, on a belt, or on a key ring. They are equipped with a very sensitive antenna/receiver, that is able to pick up signals even when there is not a direct view of the sky. We recruited 57 households to undertake the survey. This contained 136 people that were given devices or a total of 176 individuals (including children who were too young to take GPS devices). Of those, 50 households actually accepted and returned GPS devices with 107 people recording at least *some* data. We did not get complete household and vehicle information from nine households out of the 57 recruited. After a careful review of the GPS data provided, we determined that we had 42 households, containing 127 people, who provided GPS data that were considered sufficiently complete to continue into our analysis.

Table 1 provides some comparative statistics for the households that we deemed sufficiently complete to retain for analysis purposes. We show comparisons between the panel members and data from the 2001 Census and the 1999 Adelaide Household Travel Survey (AHTS), because these households were all drawn from the western suburbs of Adelaide. As can be seen from the table, our panel members have a larger average household size than the census and also than the AHTS, which itself showed a larger average household size than the census. The panel households also own more cars than both AHTS and the census, as shown by the average number of vehicles per household, where AHTS was also higher than the census. On the average number of adults, the panel is fairly close to the census, with AHTS being lower than census and the panel higher than census. However, the increased average household size is clearly largely a function of including a disproportionate number of households with children, because both the average number of children is higher and the average proportion of adults in the population is lower than the census. The average numbers of males and females are almost the same as the AHTS and slightly higher than the census. There are more workers per household in the panel than in the census, which is probably partly due to the larger average household size, but the census has 32.6 percent of

adults as full-time workers, while the panel has 43.1 percent, which may indicate a difference in the economy and the rate of unemployment at the times of the census and the panel. Finally, the higher number of students per household in the panel is consistent with the higher number of children per household in the panel. In the census, the ratio of full-time students to children is 0.85, and in the panel, it is 1.17. This suggests that the panel has captured a larger number of adult students than the census or the AHTS.

Table 1: Comparison of the Demographics for the GPS Households in South Australia with 2001 Census Data for All Households* and the Adelaide Household Travel Survey

Demographic (per household)	South Australia Statistics		
	2001 Census – All Households	Adelaide Household Travel Survey (1999)	Wave 1 50 Household Panel
Average Number of Persons	2.37	2.46	3.09
Average Number of Vehicles	1.36	1.56	1.91
Average Number of Adults	1.90	1.82	2.11
Proportion of Population Adults	80.3%	75.6%	71.6%
Average Number of Children	0.47	0.59	0.84
Proportion of Population Children	19.7%	24.3%	28.5%
Average Number of Males	1.15	1.16	1.19
Average Number of Females	1.22	1.25	1.33
Average Number of Full-Time Workers	0.62	0.70	0.91
Average Number of Full-Time Students	0.40	0.47	0.98

* The South Australia census statistics are obtained by aggregating the Western Adelaide Statistical Subdivision (SSD 40510) with the Statistical Local Areas of Holdfast Bay North (SLA 405202601) and Holdfast Bay South (SLA 405202604) to approximate the evaluation zone.

Turning now to the number of days of GPS data, Table 2 provides details of the extent to which respondents complied with the requested task of carrying the GPS device with them for 28 days. Table 2 provides statistics for 50 households. The individuals who provided more than 0 but less than 1 day per week were subsequently removed, as not having provided sufficient data to be worth retaining in the analysis.

Table 2: Number of Days for Which Data Were Recorded (Persons)

Number of Days	One-Month Panel
All days	1 (1%)
6 to less than 7 days per week	13 (12%)
5 to less than 6 days per week	10 (9%)
3 to less than 5 days per week	27 (25%)
1 to less than 3 days per week	32 (30%)
More than 0 but less than 1 day per week	24 (22%)
Total	107 (100%)

As can be seen from Table 2, only one person actually provided an entire 28 consecutive days of data. Thirteen individuals provided more than an average of six days, and a further ten individuals provided more than five and up to six days of data per week on average. We anticipate about twenty percent non-mobility, meaning that on average,

people would be expected not to travel on about 6 of the 28 days. This means that we should probably consider as complete anyone providing an average of 22 days or more of data, or an average of 5.5 days per week (of course, some may provide more and some less and still be complete).

2.1 Analysis of non-travel days

This leads into our decisions on distinguishing between travel days where no GPS record is obtained and travel days where no travel actually took place. The uncertainty concerning days missing is problematic, because the presence of no travel days has a major impact on the results of any analysis. For example in these 28-day data, 136 people received a GPS so we should have collected 3,808 days of data (=136*28). In fact, we collected only 1,305 days, or about 34 percent of the total survey days. Hence, this demonstrates the importance of knowing whether a day with no data is missing data (the person did not carry a charged device), or if it is a no travel day. Based on other evidence (Stopher *et al.*, 2006a), we could expect about 20 percent of weekdays to be genuine no-travel days. This would reduce the expected 3,808 to 3,264 days of data. There is no information currently available about expected no travel days on weekends. If we assume a rather more lenient figure of 50 percent of no travel days on weekends, this would further reduce our expected total to 2,720 days of data. Clearly, what we achieved here, which is about 48 percent of this expected total, still falls far short, so it is important to distinguish between genuine no-travel days and missing data days. In actuality, of the 136 people who received a GPS device, only 107 returned a GPS device with useable data. Given that, our potential maximum number of days drops to 2,996 and, after allowing for genuine non-mobility, our total number of person days would drop to an expected 2,140.

If an individual is a full-time worker, we would normally expect this person to travel on at least five days per week, unless he or she is employed at home. Similarly, a person who is a full-time student should normally travel on at least four days per week. On the other hand, if a person is retired or is a full-time homemaker, it is quite plausible that such a person may only travel once or twice a week. Taking into account the work or student status of each person, the type of work in which he or she is engaged, age, and whether or not the person works at home, we devised a set of rules relating to the number of days that we felt there could be genuine absence of travel. Table 3 provides a summary of these rules. The categories of work and student status are not mutually exclusive. If a person falls into more than one category, then the more stringent one is assumed to apply. These rules were developed from logic and a consideration of the likely travel situation for people in the various categories. It is not based on empirical observation.

Using these rules, missing days were recoded to either indicate a legitimate no-travel day, or a missing day. As can be seen from a cursory examination of Table 3, if a person was missing data for seven consecutive days, then at least one such day would be considered to be a missed travel day, depending on the category into which the person falls.

In processing the data, we found it necessary first to remove 32 people from the 107, representing 86 days of data, because these people used the GPS so little, it was not possible to process them further in this analysis. (For other analyses, their data could still be potentially useful.) If a person started using the device one or more days after the anticipated start date, or ended using the GPS one or more days before the end of the 28-day period, we ignored those missing days. Thus, a person whose first data were for the third day after the start of the 28-day period, and whose last data were recorded three days before the end of the 28-day period, was assumed to have been measured for a period of 24 days, and only missing days within those 24 were considered for resolution between missing and no travel. We then counted all missing days between the first valid GPS record and the last. This totalled 525 days. After applying the rules, we determined that 359 of these were probably valid no travel days, and 166 were days of missing travel data. Splitting those

between weekdays and weekends, we had 334 weekdays missing and 191 weekend days missing, of which 209 weekdays and 150 weekend days were considered to be genuine no-travel days. This produces non-mobility rates of 19 percent for weekdays and 33 percent for weekend days, which appear very plausible values. Total valid days of data are then 1,578, including genuine no-travel days.

Table 3: Plausible Maximum Number of Days for which a Person Could Have Stayed at Home

Ref. No.	Work/ Student Status	Work at home	Type of work*	Age	other measures	Total missing days allowable in a week (Saturday to Friday)	Total consecutive missing days allowable	Total missing weekdays allowable in a week (Saturday to Friday)	Consecutive missing weekdays allowable
1	Employed/ Homemaker	yes	All	<65		5	5	5	5
2	All, not retired	-	All	<65	HH size=1	3	3	3	3
3	All	-	All	<65	<16 years old in HH	3	3	3	3
4a	Full-Time Student	-	-	<17		3	3	1	1
4b	Full-Time Student	-	-	>17		4	3	2	2
5	Part-Time Student	-	-	all		4	4	3	3
6a	Full-Time Employed	no	1	all		3	3	2	1
6b	Full-Time Employed	no	2	all		3	3	3	3
6c	Full-Time Employed	no	3	all		4	4	4	4
7a	Full-Time Employed/ Student	no	1	all		2	2	1	1
7b	Full-Time Employed/ Student	no	2	all		2	2	2	2
7c	Full-Time Employed/ Student	no	3	all		4	3	2	2
8a	Full-Time Employed/ Part-Time student	no	1	all		3	2	1	1
8b	Full-Time Employed/ Part-Time student	no	2	all		3	2	3	2
8c	Full-Time Employed/ Part-Time student	no	3	all		4	4	3	3
9a	Part-Time Employed	no	1	all		4	4	3	3
9b	Part-Time Employed	no	2 & 3	all		4	4	4	4
10	Full-Time Student/ Part-Time Employed	no	1, 2 & 3	all		3	3	2	2
11a	Part-Time Student/ Employed	no	1	all		4	3	3	2
11b	Part-Time Student/ Employed	no	2 & 3	all		4	3	3	3
12	Employed Casually	no				4	4	4	4
13	Self Employed	no				4	3	4	3
14	Homemaker/ Retired			>65		6	6	5	5
15	Regular Volunteer Worker					5	4	5	4
16	Unemployed and Actively Seeking Work					4	3	4	3

* type of work:

1. A job that requires the person's presence normally from Monday to Friday (normal days, normal hours) [e.g., clerical,...]
2. A job that permits the person to have days off in the weekdays, not obligatory on Saturdays and Sundays.
 - a. The days off are invariable [e.g., salesman,...]
 - b. The days off are variable [e.g., plumber, electrician,...]
3. A job that gives the person probably more than 2 days off in a week and not obligatory on weekends.
 - a. The days off are invariable [e.g., teacher, lecturer,...]
 - b. The days off are variable [e.g., airline pilot,...]

2.2 Data Analysis

In our subsequent analysis, we chose to increase the sample sizes we could use by looking at either all those people who had at least 21 days of good data (including accepted no travel days) or those people who had at least 15 days of good data (also including accepted no travel days). This gave us samples of 44 people who gave us at least 21 days of good data, and 65 people who gave us at least 15 days of good data. However, for our analyses

we removed two people (from different households) who had unusually high trip rates. Our analysis focused on five principal measures: person kilometres of travel (PKT) per day, number of trips per day, travel time per person per day, average travel time per trip, and average travel distance per trip. Although we are able to process the data and identify the mode of travel, for the purposes of this analysis, we have not considered mode. Also, purpose of travel, which is also largely possible to determine, has not been used in the analysis.

We processed the raw GPS data and split the data for each person for each day into trips, based on a series of heuristic rules (FitzGerald et al., 2006). Following the data processing, we undertake a manual check of each day of data for each person, to determine whether the identification of trips appears sensible or not. In those cases where it appears that the software has identified as a trip some spurious data, has assigned a trip-end to an intermediate stop in a trip, or there is a missing trip (evidenced by a trip ending at one location, and then the next trip beginning from a completely new location), manual edits are made to the trip records. In processing the data for this sample, we started with 6,577 trips that were identified by the software. After manual checking, this number decreased to 6,485. In this process, we deleted about 698 spurious trips and added about 606 trips, so that the total number of trips decreased by 92. The trip-end of about 285 trips were identified as false and were hence extended. (Our software has subsequently been improved, so that fewer manual corrections are needed in our latest version.)

In the following sections, we first report on a number of analyses we performed in which we examined patterns of variability over the period of 21 days. Then, following similar procedures to those developed by Pas (1987) and implemented by Muthyalagari *et al.* (2001) and Pendyala (2003), we examine the intra- and inter-personal variability exhibited in the data.

3 Day-to-day variability

3.1 Analysis of 21 days of data

We commenced our analysis by looking at the five measures of PKT per day, trips per day, travel time per day, and average time and distance per trip. The first thing that is interesting to look at is what happens to the averages of each of these statistics as the number of days of observation increases. For those persons who provided at least 21 days of data, the variation in the mean person kilometres of travel per day is shown in Figure 1 and for trips per person per day, it is shown in Figure 2.

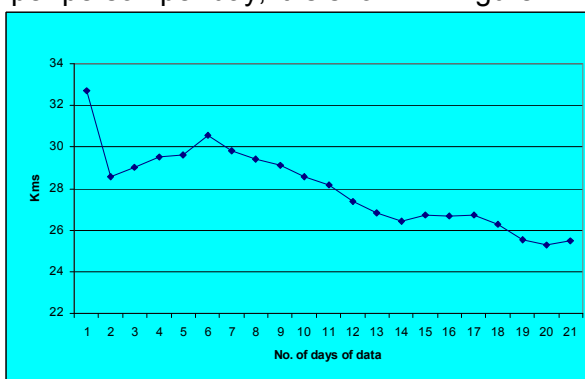


Figure 1: Variation in Mean PKT per Day

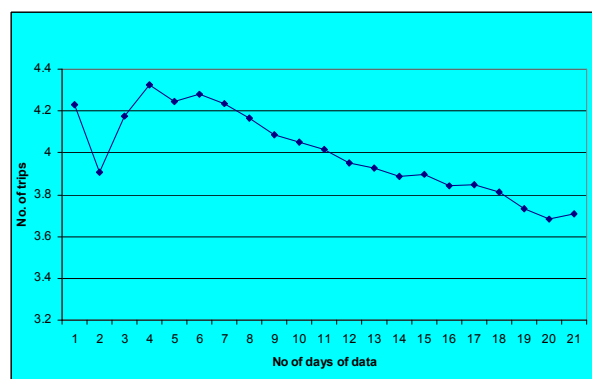


Figure 2: Variation in Mean Trips per Day

In both cases, there is some wide variation in the first few days, after which the values of each of PKT per day and trips per day decline slowly, and level off at the end of the period. It must be borne in mind that people would start their GPS recording period on any day of the week, although more likely on Tuesday through Saturday, because the courier deliveries were usually made on Monday through Friday.

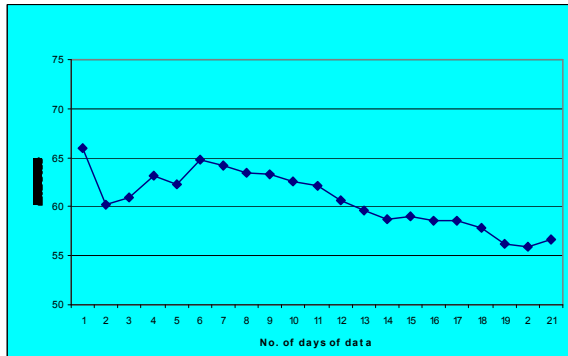


Figure 3: Variation in Mean Travel Time Per Day

Over the first four or five days, the mean changes fairly substantially, as variable behaviour is recorded. However, as the time period becomes longer, the mean settles down to a more gradual change, and the continuing decline appears to be the result of a build up of weekend days, in particular, and also of genuine no travel days, that cause a slow decline in the mean value. It is very interesting to note that the first day of data shows results that are similar to those reported elsewhere for standard one-day travel surveys (e.g., Stopher and Metcalf, 1996), such as an average person trip rate of just over 4.2, and about 66 minutes per day of total travel time. However, the stable mean is in significant contrast to these values, showing the trip making stabilises at about 3.72 trips per person per day, and total daily travel time stabilises to about 57 minutes. Both of these are seven-day week averages.

Figure 3 shows the same presentation for travel time per person per day. These graphs tend to suggest that averages based on one day of data will be too high for all three of these variables, and also suggest that the value does not stabilise until we have about 18 or 19 days of data, by which time further declines are small and the mean values vary relatively little as the measurement period is extended. While the initial pattern for trip time and trip distance per trip are somewhat different, they exhibit a similar pattern of decline and stabilisation.

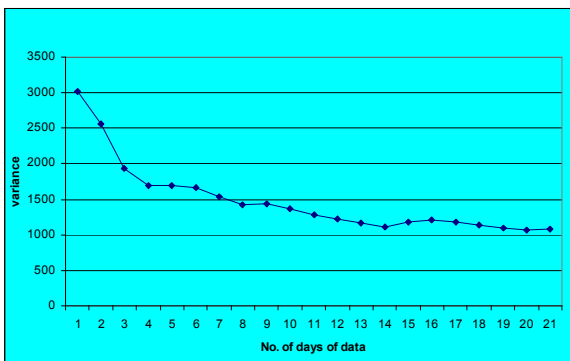


Figure 4: Variation in Variance of PKT by Days of Data

Similarly, we examined the variation in the variance of these five statistics and found a pattern in which the variance also tended to be highest on the first day, and then it gradually stabilised in value, as shown, for example, by Figure 4. In this case, the variance declines quite substantially for the first four days and then stabilises fairly well by about the fourteenth day. Interestingly, we found that each of the variances exhibited stability by around the fourteenth day. Additional graphs of this type are shown in Stopher *et al.* (2006b).

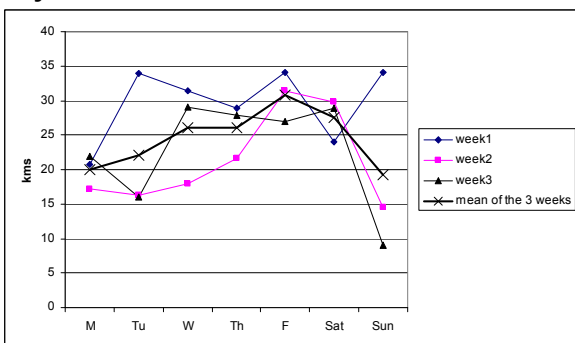


Figure 5: Variation of PKT by Day of Week and Week of Survey

The next analysis we undertook was to look at differences in means and variances by day of week and week of the survey for these same persons. The variation in PKT per person per day by day of week and week of survey is shown in Figure 5. It should be borne in mind that the households contributing to these data started the GPS survey on different days of the week and on different weeks within the period between October and November 2005. In Australia, there were no holidays that would have made one week different from other weeks

in this period. Two of the three weeks show Sunday as having the lowest average PKT per day, while the other week shows Sunday with an equal highest value, together with Tuesday and Friday of that week. On average, Sunday is the lowest for the whole week. Monday has a similar low value in all three weeks and on average. Tuesday of weeks 2 and 3 are identical and second lowest to Sunday, but in week 1, Tuesday is one of the highest figures. Friday shows a peak in weeks 1 and 2, but shows a decline from Wednesday and Thursday in week 3. On average, PKT appears to climb through the week to a high on Friday, then

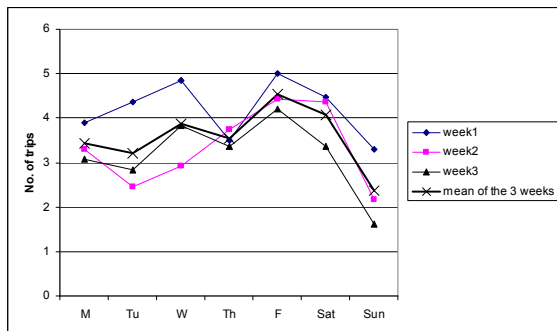


Figure 6: Variation in Person Trips by Day of Week and Week of Survey

dropping to a low on Sunday. The variation in person trips, shown in Figure 6, is more regular and understandable. Here, we see that Sunday has the fewest trips per person in all three weeks and on average, and Thursday shows a very consistent number between the three weeks. Among the weekdays, Friday has one of the highest values of trips per person in all three weeks, and Saturday shows only a small decline below Friday in each week. In two of the three weeks, Wednesday also shows a high figure, while week 2 shows a steady climb in numbers of trips per person from Tuesday to Friday. Interestingly, we also found that

Wednesday of the second week had a high value of no travel days, whereas this was not exhibited in the other two weeks. On the average, the number of trips drops from Monday to Tuesday, climbs to Wednesday, drops to Thursday, climbs to Friday and then drops back on Saturday and more on Sunday.

A graph of the no travel days is shown in Figure 7. It should be kept in mind that there are 42 observations in these graphs, so that a number of no travel days of 23, such as occurs in the Sunday of week 3, implies that half of the sample did not travel on that day, and that the person trips are based on 21 people travelling and 23 not travelling, and similarly for the PKT in Figure 5. In general, the pattern of no travel days appears to start high on Monday, then decline slightly to Tuesday and Wednesday, followed by a sharp rise on Thursday in two of the three weeks, and a drop on Friday. Saturday tends to be higher than Monday and Thursday, and Sunday is the highest. Overall, the no travel days appears to run opposite to the trend in trips, with a decline through the weekdays and a rise on the weekend, much as would be expected.

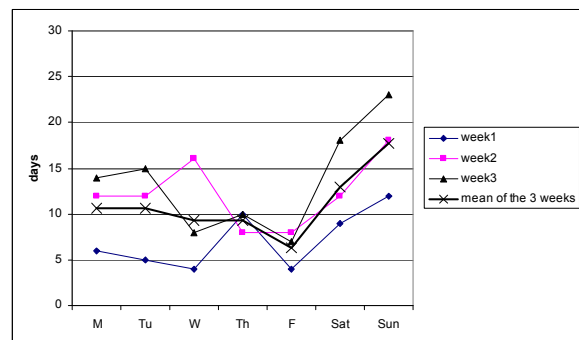


Figure 7: Number of No Travel Days by Day of Week and Week of Survey

3.2 Halo effects

Looking at the graphs presented thus far, one is tempted to wonder if the instability in the first three or four days may have something to do with the halo effects of asking people to carry GPS devices with them. To check on this, we repeated our analyses for a more restricted data set. In this case, we chose to use a sample of people who provided at least fifteen days of data, but then ignored the first three days and the last two days, so that we graphed only days 4 to 13. Space does not permit us to display all of these graphical results. However, Figure 8 shows the result for PKT per day. While the lines converge, the differences between the first two or three days and the stable result as we move out towards ten days are more marked for the 4 to 13 day data, than for the first ten days of data.

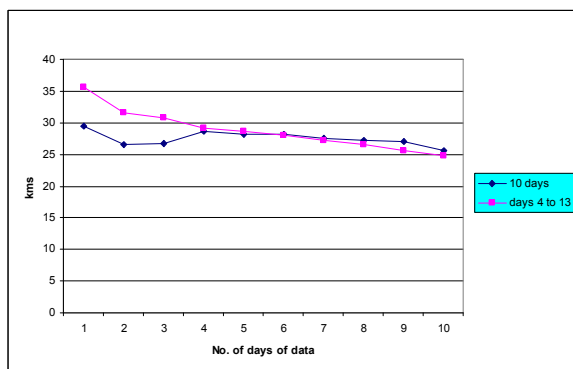


Figure 8: Comparison of Variance for first 10 Days and Days 4 to 13 – PKT per person per day

Looking at the effects on the variance, we obtained the graph shown in Figure 9. The variance for the first ten days is not the same as we obtained for the first 21 days of data (a smaller data set), shown in Figure 4. However, the data for 4 to 13 days is almost exactly the same in shape as that shown in Figure 4. We repeated this analysis for all five critical variables, but found similar results. The data from 4 to 13 days generally produced very similar graphs to the full 21 days, with a large value at the outset declining to a smaller and stable value as the time period became longer.

From this analysis, we conclude that there is no evidence of halo effects from carrying the GPS device on such measures as the number of trips, the total travel time in the day, the distance and time per trip, and the total person kilometres of travel.

3.3 Conclusions on the multi-day analyses

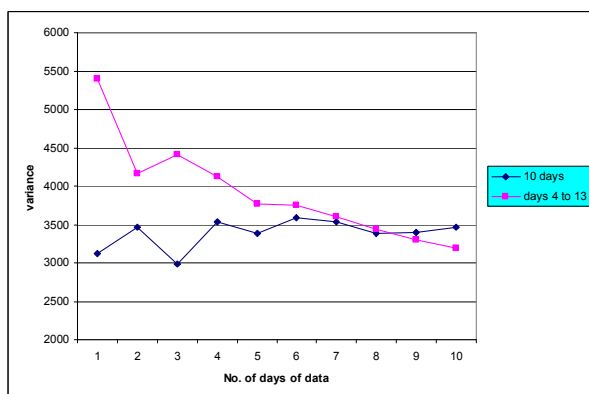


Figure 9: Variation in Variance of PKT for 4 to 13 Days and First 10 Days

One of the main conclusions to be drawn from these graphs is that there is a great deal of day-to-day variability in travel, which is clearly not captured in one and two day travel surveys. Not only that, but it would appear that one-day and two-day travel diaries will probably overestimate average daily trip rates, and PKT per day. On the other hand, we can also see that there may not be substantial gains in prolonging the measurement beyond about two weeks or so. The means and variances of the critical variables appear to become stable at somewhere around 14-18 days of observation, and we also have observed

that there are problems in having people comply with the request to carry GPS devices for as long as 28 days. Hence, we might conclude that about 15 days of measurement may represent the optimum, considering both the day-to-day variability and the willingness of people to comply with the survey request.

4 Intrapersonal and interpersonal variability

We can consider that the total variability in day-to-day travel behaviour that has been examined in the previous section is composed of two elements. The first of these is the interpersonal or between person variability. This has to do with differences among people in the way in which they behave. The second element is the intrapersonal variability, which is the variability in each person's day-to-day behaviour. While each of these two elements of variability could be subdivided further, we have not done so at this time. There are, however, two goals of the analysis that we report here: first is to investigate if there is a day of week effect on intrapersonal variability, and the second is to investigate the effects of the period of observation on the estimates of intrapersonal variability. Determining the intrapersonal variability is done by estimating a mean for each person on each critical variable, and then

estimating the sum of squares for each individual about the person mean. We used a sample of 63 persons for this analysis, where all of these persons provided at least 15 days of data (including valid no travel days). For each analysis, we can estimate the ratio of the intrapersonal sum of squares to the total sum of squares, from which we can conclude how much of the total variability is attributable to within-person variability and how much to between-person variability.

First, we estimated the intrapersonal and total sums of squares for the first 15 days of data for the sample of 63 individuals. Then, we estimated the same two numbers for just the weekdays in those two weeks, and then we looked at just the first week of analysis for both all days and weekdays. The first of these two, when compared to the full two weeks, would indicate if there is an effect of weekdays versus weekend days, whilst the second indicates whether the longer period of observation (two weeks) changes the effect of intrapersonal variability. We analysed three critical variables: the number of person trips per day, the person kilometres of travel per day, and the total person travel time per day. The results are shown in Figure 10.

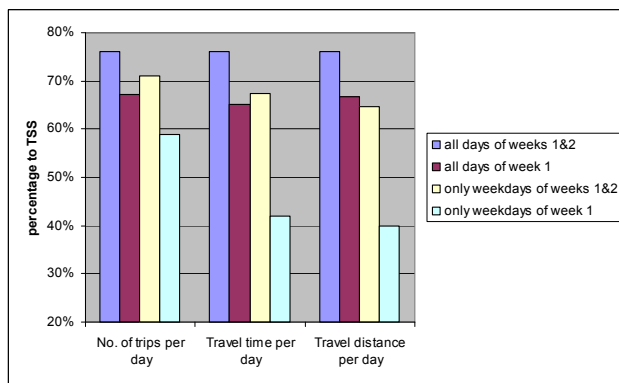


Figure 10: Importance of Intrapersonal Variability in the Total Day-to-Day Variability

For all three variables, Figure 10 shows that the intrapersonal variability accounts for about 76 percent of total variability, when we look at the entire data set of 63 individuals for 15 days (indicating that 24 percent of the variability was a result of interpersonal variability). However, when we restrict the data to weekdays only, the intrapersonal variability drops to between 64 and 71 percent, depending on the variable being considered. This is much as we expect. It suggests that there is more regularity in each person's behaviour during the five weekdays than on the two weekend days, so that the contribution of intrapersonal variability on weekdays only is smaller than for all days taken together.

For all three variables, the proportion of the variability that is contributed by intrapersonal variability is smaller for the first week than for the two-week period, especially for weekdays only, where the differences are large. This would suggest that the longer period of observation allows the measurement of more of the intrapersonal variability, than the shorter period. These findings are consistent with those reported by Pendyala (2003), Pas (1987) and Pas and Sundar (1995). Using data for three to five days, Pendyala found that the amount of variability accounted for by intrapersonal variability was around 70 percent for

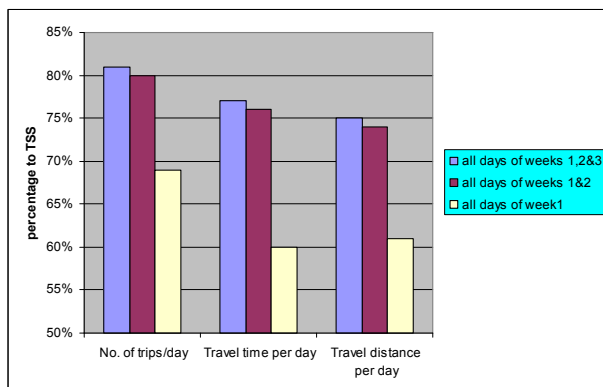


Figure 11: Comparison of 1, 2, and 3 Weeks of Data

VKT and total trips, while it was around 61 percent for in-vehicle travel time. He also found that it dropped for weekdays only, to around 60 to 68 percent, and for a shorter observation period to around 50 to 64 percent, depending on the critical variable.

Figure 11 shows the comparison of the amount that intrapersonal variability accounts for out of total variability for the sample of 42 persons for whom we have at least 21 days of data. This shows that there is a huge increase in the share of intrapersonal variability from one week to two weeks, but only a slight increase from

two weeks to three weeks. Indeed, from two weeks to three weeks, the increase is only about one percent.

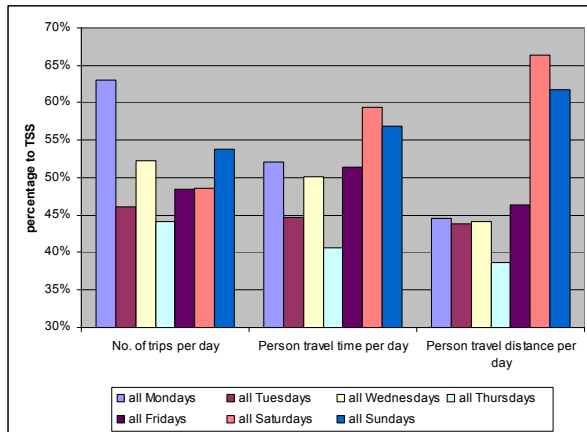


Figure 12: Variation in Intrapersonal Variance by Day of Week

Finally, Figure 12 shows the variation in the intrapersonal variability proportion by day of week over three weeks. In Figure 10, the intrapersonal variability for weekdays only accounted for around 64 to 71 percent over two weeks. In this case, for the weekdays, the intrapersonal variability over three weeks accounts for generally less than 50 percent of the total variability, showing that variance by day of week is actually an important component of the total variance. The contribution of intrapersonal variability is much lower by day of week than it is for all weekdays taken together.

5 Conclusions

From the analyses discussed in this paper, we can draw several conclusions. Probably the overwhelming most important conclusion is that travel surveys that measure only one or two days of data for urban travel provide overestimates of both the means and variances of such measures as person kilometres of travel per day, number of trips per day, time spent travelling per day, as well as average time and distance per trip. In our analyses of these variables, we found that increasing the numbers of days of observation led in all cases to a decline in the value that was rapid over the first few days and then slowed to a much more gradual decline, with stability generally being reached after about 18 to 19 days of observation. On the other hand, we also noted that it was difficult to get people to carry GPS devices for as long as 28 days and to do so diligently throughout the period. In contrast, we have found a much higher rate of compliance with seven-day GPS surveys. This suggests that a compromise may be preferable in which people are asked to carry GPS devices with them for all travel for about 15 days.

Because of the decline in values of the means and variance for the first three or four days, we also investigated the possibility that we were seeing a halo effect, resulting from being asked to carry a GPS device. However, when we graphed the means and variances, after discarding the first three days of use of the GPS, we continued to find the same pattern of decline in the means and variances. This suggests that it is not a halo effect we are seeing, but simply the fact that the variability in any one day is high, and that averaging over multiple days reduces the value steadily.

We also examined the question of intrapersonal variability (which cannot be measured in a one or two day travel survey) to determine if the day of week affects the proportion of total variability that is attributed to intrapersonal variability, and also to determine if the length of time for which people are observed affects this proportion. In both cases, we came to an affirmative conclusion. The proportion of the total variability that is a result of intrapersonal variability is smaller if we compare weekdays to all days, or one week to two weeks. It is also smaller if we compare day of week to week days or all days.

We conclude that GPS data produce results that are consistent with prior expectations about the variability in travel behaviour. We also conclude that longer periods of observation of travel behaviour will lead to more consistent models and analyses, because the amount of

variability recorded from one or two days only overstates the true situation. Indeed, we believe that, while the GPS data for multiple days would provide smaller amounts of variance in the data for modelling, this is likely to lead to better models, because we would have removed some unexplained variance that is an artefact of measuring travel behaviour for only one or two days. This unexplained variance is almost certainly a contributor to the variance that models cannot explain, and may also distort the relationships that are developed in much of our travel demand modelling.

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