Transportation **18**: 383–409, 1991

Impact of telecommuting on spatial and temporal patterns of household travel

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Received 13 June 1991; accepted 5 August 1991

Key words: action space, impact assessment, panel survey, spatial analysis, telecommuting, temporal distribution

Abstract. A spatial and temporal analysis of travel diary data collected during the State of California Telecommuting Pilot Project is performed to determine the impacts of telecommuting on household travel behavior. The analysis is based on geocoded trip data where missing trips and trip attributes have been augmented to the extent possible. The results confirm the earlier finding that the Pilot Project telecommuters substantially reduced travel; on telecommuting days, the telecommuters made virtually no commute trips, reduced peak-period trips by 60%, total distance traveled by 75%, and freeway miles by 90%. The spatial analysis of the trip records has shown that the telecommuters chose non-work destinations that are closer to home; they exhibited contracted action spaces after the introduction of telecommuting. Importantly, this contraction took place on both telecommuting days and commuting days. The telecommuters distributed their trips, over the day and avoided peak-period travel on telecommuting days. Non-work trips, however, show similar patterns of temporal distribution on telecommuting days and commuting days. Non-work trips continued to be made during the lunch period and late afternoon and evening hours.

Introduction

Lifestyle plays a major role in determining travel behavior. It is then possible that insights into changes in travel patterns can be obtained by examining changes in lifestyles. However, opportunities to study changes in lifestyle and concomitant changes in travel behavior are rare. A unique opportunity to describe changes in household travel behavior that arise from a change in lifestyle is offered by telecommuting. The use of telecommunications to substitute for the commute to work has recently drawn extensive attention as a strategy for reducing travel demand. This came to be known as telecommuting, broadly defined as "the partial or total substitution of telecommunication, with or without the assistance of computers, for the twice-daily commute to/from work" (Nilles 1988).

Telecommuting entails a certain amount of change in the lifestyle of a person. The telecommuter now works at home and can allocate time to various tasks with increased flexibility. Telecommuting releases some of the work-related constraints such as the commute to and from work and the lunch hour which usually take place according to a fixed schedule. This added flexibility in a telecommuter's life, as a result of the relaxation of time-space constraints, may lead to changes in the travel behavior of not only telecommuters, but also their household members (Garrison & Deakin 1988). An accurate assessment of these changes is necessary to determine whether telecommuting is an effective travel demand management technique.

The State of California Telecommuting Pilot Project was started in 1988 to evaluate the feasibility and effectiveness of telecommuting within State government agencies (JALA Associates 1985). As part of this project, a three-day travel diary was distributed in 1988 and 1989 to assess the changes in household travel patterns due to telecommuting. In the diary survey, the participants and driving-age members of their households were requested to report detailed information on the trips they made on three consecutive survey days. In the second round, the employees who were selected to telecommute had started doing so and this facilitated a "before-and-after" analysis.

Trips are generated by a person's need to perform activities at different locations at various times of the day. Useful insights into individual and household travel demand can be obtained by studying individual activity engagement and trip making patterns. If the trip-generating activities are studied over a multi-day period, then it would be possible to see how an individual allocates activities among the days. At the household level, it would be possible to see how household members allocate their tasks among themselves.

In the short run, it is conceivable that telecommuting will reduce the number of work trips, which will in turn reduce the peak period traffic and vehicle miles traveled. However, this reduction coupled with the added flexibility in scheduling could lead to the generation of new discretionary trips that the telecommuter did not make before.

Another possible outcome is that a telecommuter may be choosing different destinations and different times of the day to pursue activities. For example, shopping and other activities that were previously done during the commute trips in the peak period may now be pursued independently from home, possibly at different locations and at different times of the day. Also, tasks that were previously performed by the household members may now be assigned to the telecommuters as they have gained additional discretionary time.

Under normal commuting situations, the time of day distribution of trips involves two peaks – one in the morning and one in the afternoon. It is necessary to see how telecommuters choose to distribute their activities over the day to assess the impacts of telecommuting on peak period trip generation. Will they spread out their activities and trips such that the peaks are flattened, or will they continue making trips during those periods by force of habit? Or will they take on other household tasks which need to be performed at peak periods such as dropping off and picking up children at school, thus giving no benefits to peak period traffic conditions? Answers to these questions will prove useful in addressing not only congestion but also air quality and energy impacts (Horowitz 1982).

Changes in mode use are also probable. The irregular commuting schedules may make car-pooling difficult for telecommuters, who could switch to driving alone to work. The presence of an additional car at home on telecommuting days could induce household members to switch mode too In the long term, this switch in mode use may induce changes in car ownership levels.

This paper aims at assessing the impacts of telecommuting on household travel behavior. Its objectives are twofold. Firstly, the study attempts to confirm the trip reduction effects of telecommuting reported earlier (Kitamura et al. 1990a, b) through a detailed analysis of the quality of trip reporting in the three-day travel diary survey. Secondly, the study extends the previous analyses by examining changes in spatial and temporal characteristics of travel patterns that are due to telecommuting. All trip origins and destinations were geocoded to facilitate the spatial analysis of trip making. Given the one year timeframe of the survey, this paper assesses the short term impacts of telecommuting.

First, trip-activity profiles showing the details of every trip and activity performed by an individual over the survey period were constructed and used to augment missing information. The profiles involved chronologically ordering all trips and activities pursued by an individual. Missing trips or activities which resulted in an interruption of the sequence were identified and augmented. Also, trip attributes such as origin, destination, and duration, were imputed wherever logically possible using information available in the reported trips. This effort was undertaken to account as much as possible for the potential effects of trip reporting errors, which are common in multiday panel travel diary surveys of this type (Golob & Meurs 1986; Meurs et al. 1989; Pas 1986).

The preliminary spatial analysis was performed on the augmented geocoded data in an effort to capture the effect of telecommuting on destination choice and household task allocation. The spatial analysis provides useful insights into the trip distribution patterns that emerge as a result of telecommuting. The temporal analysis presented in this paper examines the distribution of activities by time of day.

The next section describes the State of California Telecommuting Pilot Project and the study sample. This is followed by a description of the data files and the procedures followed for geocoding and the maximum retrieval of information. The analysis of travel characteristics is presented in the fourth section. The fifth section describes the results of the spatial and temporal analysis of trip making. Finally, the conclusions are presented in the last section.

The State of California Telecommuting Pilot Project

The State of California Telecommuting Pilot Project (JALA Associates 1990) involved conducting a panel travel diary survey at two time points with the intent of evaluating the impacts of telecommuting on household travel (Kitamura et al. 1990b). The first wave of the survey was administered in 1988 and the second wave in 1989. In the first wave, all respondents were asked to fill out the diaries on Wednesday, Thursday, and Friday. In the second wave, no such restriction was imposed, except that the three survey days must be three consecutive weekdays. An additional restriction imposed on the telecommuting group was that at least one of the days must be a telecommuting day.

The sample of the study in the first wave comprised 269 state employees who participated in the Pilot Project on a voluntary basis and 178 of their household members who were of driving age. Of the 269 project participants, 17 returned unusable diaries (diaries containing no information) in the first wave of the survey, which yielded a first wave respondent employee sample of 252.

This sample consisted of 137 experimental telecommuter group employees, and 115 control group employees. All the participants were asked to record trip characteristics in three-day travel diaries both in 1988 and 1989. In the first wave of the survey, all employees commuted to work conventionally, while in the second wave, the telecommuter group had commenced telecommuting. Thus, travel characteristics were measured before and after the introduction of telecommuting. The presence of the control group allowed the isolation of the impacts of telecommuting on telecommuter household travel patterns.

Attrition is evident in this panel study. In the second wave, a total of 257 persons (159 households) responded. However, of the 430 persons who

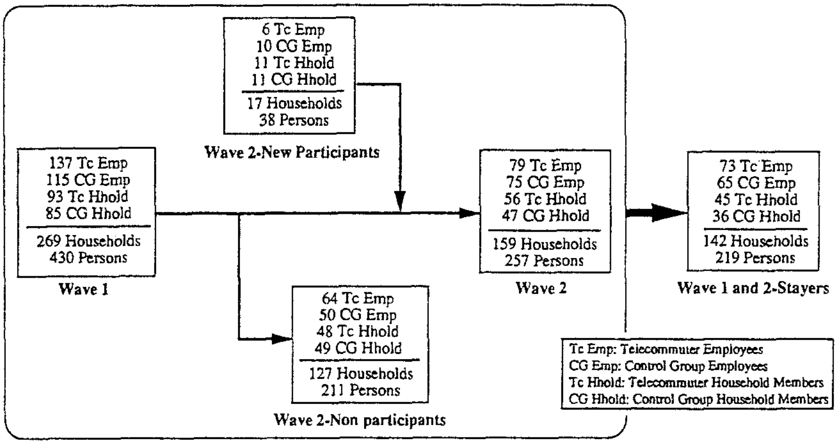

Fig. 1. Evolution of the Study Sample.

had usable responses in the first wave, information on both waves was available for only 219 persons. These respondents will be referred to as 'stayers' in this paper. The stayer sample is made up of 73 telecommuter employees, 65 control group employees, 45 telecommuter household members and 36 control group household members. Those who did not respond in the second wave include those who did not return diaries or returned unusable diaries, and those who left the project due to retirement, promotion, etc. The additional respondents in the second wave (38 persons for whom first-wave

Table 1. Distribution of respondents by gender.

	Gender	
Sample Group	Male	Female
Telecommuter Employees (N=73)	47 (65%)	25 (35%)
Control group Employees (N=65)	40 (64%)	23 (36%)
Telecommuter Household Members (N=45)	11 (26%)	32 (74%)
Control group household Members (N=36)	11 (31%)	24 (69%)

Note: 6 respondents had missing information.

information is not available) include new project participants and participants who did not return diaries or returned unusable diaries in the first wave. Fig. 1 shows the transition of the sample from the first wave to the second wave and finally to the stayer sample.

Stayer sample descriptive characteristics

Tables 1 through 5 provide descriptive characteristics of the stayer sample used in this study. In Table 1, the distribution of respondents by gender is found to be approximately equal between the telecommuter and control groups. While the state employees are found to be predominantly male, the household members tend to be predominantly female.

The household size distribution is shown in Table 2. It can be seen that the average household size for telecommuter households is slightly larger than that of control group households. While 31% of control group households are single-person households, the corresponding percentage for telecommuters is 22%. Forty percent of telecommuter households have more

Table 2. Household size distribution (First Wave).

	Household size				
Sample group	1	2	3	>3	Weighted average
Telecommuter (N=75)	16 (22%)	28 (38%)	13 (18%)	16 (22%)	2.40
Control group (N=67)	20 (31%)	23 (35%)	9 (14%)	13 (20%)	2.23

Note: 4 households had missing information. $\chi^2 = 1.514$, df = 3, p = 0.68. Household size is not available for the second wave.

than two members, while only 34% of control group households have more than two members. This suggests that more telecommuter households have children than control group households. However the household size distributions are not significantly different between the two groups (at a 5% level).

The control group households own fewer cars than telecommuter households (Table 3), which is commensurate with the smaller household size they exhibit. This suggests that telecommuter households tend to be more auto-dependent to pursue activities. There is a small increase in car ownership across the waves for both groups. Telecommuting does not seem to have motivated telecommuter households to discard a vehicle in the short term (1 year span of this survey). In the second wave, 71% of telecommuter households own two or more cars, while the corresponding percentage for control group members is only 57%. The chi-square statistics to test equality of proportions show that the distributions of car ownership are not significantly different between the groups.

The distributions of monthly incomes for the participating employees are

Table 3. Household car ownership distribution.

Sample group	Wave	Car ownership				Weighted average
		0	1	2	>2	
Telecommuter (N=75)	Wave-1	0 (0%)	26 (36%)	33 (46%)	13 (18%)	1.74
	Wave-2	0 (0%)	21 (29%)	42 (58%)	9 (13%)	1.78
Control group (N=67)	Wave-1	6 (9%)	20 (31%)	31 (48%)	8 (12%)	1.57
	Wave-2	3 (5%)	25 (38%)	27 (42%)	10 (15%)	1.60

Note: 5 households had missing information.
The first two columns are collapsed to avoid small expected cell frequencies.
Wave-1: Telecommuter vs. Control Group–$\chi^2 = 0.898$, df = 2, p = 0.64.
Wave-2: Telecommuter vs. Control Group–$\chi^2 = 5.245$, df = 2, p = 0.07.

Table 4. Income distribution of state employees (monthly salary in First Wave).

Sample group	Income group (thousands of dollars)				
	1.5–2.5	2.5–3.5	3.5–4.5	4.5–5.5	>5.5
Telecommuter Employees (N=73)	5 (7%)	12 (16%)	35 (48%)	6 (8)%	7 (10%)
Control group employees (N=65)	3 (5%)	17 (26%)	30 (46%)	6 (9%)	2 (3%)

Note: 15 respondents had missing information for this table.
Income is not available for the second wave.
$\chi^2 = 4.139$, df = 4, p = 0.57.

very similar between the two groups (Table 4). The only noteworthy difference across the group is that a larger percentage of telecommuter employees earn more than $5,500 per month. In contrast, a larger percentage of control group members are in the middle income category earning $2,500 to $3,500 per month.

In Table 5, the age distributions of respondents are compared across the different groups. The telecommuter employees are older than their control group counterparts, while their household members are slightly younger. The higher age and income exhibited by telecommuter employees suggests that they are senior professionals in a later stage of lifecycle. This is also

Table 5. Age distribution of respondents.

	Age group					
Sample group	16-25	26-35	36-45	46-55	>55	Weighted average
Telecommuter Employees (N=73)	0 (0%)	12 (17%)	30 (43%)	21 (30%)	7 (10%)	44.13
Control group Employees (N=65)	1 (2%)	20 (31%)	20 (31%)	18 (28%)	5 (8%)	41.91
Telecommuter Household Members (N=45)	5 (11%)	10 (23%)	18 (41%)	8 (18%)	3 (7%)	38.91
Control group Household Members (N=36)	3 (8%)	7 (19%)	15 (42%)	8 (22%)	3 (8%)	40.64

Note: 5 respondents had missing information for this table.
Telecommuter Employees vs. Control Group Employees: $\chi^2 = 5.307$, df = 4, p = 0.26.

evidenced by the younger age of their household members which may be attributed to the presence of more children (recall the larger household size in Table 2). However, a test of equality of proportions showed that the age distributions are not significantly different across the employee groups.

In summary, telecommuter households differ slightly from their control group counterparts with respect to their household size, car ownership, income and age. In all of these characteristics, the telecommuter households exhibit larger values. Another important characteristic in which the telecommuter employees exhibited a larger value is with respect to the commute distance (as measured by the direct home-work distance). The telecommuter employee had an average commute 19.5 miles while the control group had an average commute of 15.4 miles. However, none of these differences are significant at a 5% level and the two groups may be considered quite similar to one another.

Data files

Two types of data files were created in each wave using the information contained in the travel diaries returned by the respondents. The first type contains personal and household information while the second type contains trip information. The person files provide socio-demographic information such as the respondent's project participant status (telecommuter or control group), age, gender, employment status, vehicle ownership and frequently used transit companies. The file also contains the addresses of the respondent's home, work, school and other frequently visited locations, which proved useful for the spatial analysis.

The trip files contain detailed characteristics of each trip reported by the respondent. The information includes the trip origin and destination, trip beginning and ending times, trip purpose, estimated trip length in miles, mode used, and, if a car was used, the beginning and ending odometer readings, the number of passengers, and the percentage of the trip spent on the freeway. The trip file from the first wave contains information on 4808 trips reported by 430 persons in 269 households while that from the second wave contains information on 2389 trips reported by 257 persons in 159 households.

Geocoding of trip ends

All trip origins and destinations along with home, work and school locations were geocoded using detailed maps obtained from the Maps Division of the California State Department of Transportation. The latitude of a location was used as its Y–coordinate and the longitude as its X–coordinate. The latitudes and longitudes were coded to the nearest second, thus providing an accuracy of ±100 feet in terms of distance. The spatial analysis, whose results are reported in the next section, was performed using this data file and offers a concise picture of the spatial spread of trip ends before and after the introduction of telecommuting.

Trip-activity profiles and data augmentation

Trip-activity profiles are constructed for each individual by sequentially arranging his trips and activities over the three day survey period. A computer program originally written by van Wissen (1989) was modified and used in this effort. The profiles contain pertinent trip information (e.g. trip length, trip duration, trip purpose, and mode used) and information on the activities pursued (e.g. type, duration, and beginning and ending times).

This ordering of information contained in the trip diaries helps in identifying and imputing missing information. For example, if it is found that a particular trip ends at home and the next trip starts from a location other than home, then it can be deduced that a trip from home to the other location is missing, and may be augmented. Thus a trip not reported by the respondent is inferred, with imputed origin and destination information. Trip durations which could not be calculated due to missing trip beginning or ending times, were imputed by dividing the trip distance by an average assumed speed of 30 mph. The intent of this augmentation was to reduce much of the bias that may result from trip under-reporting. Details on the augmentation procedure can be found in Pendyala et al. (1991).

Table 6. Summary of augmentation for stayers.

Trip characteristics	Wave	Telecom employees	Control employees	Telecom household	Control household
Reported trips	Wave-1	822	808	532	336
	Wave-2	657	756	406	329
Augmented trips	Wave-1	62 (8)	74 (9)	26 (5)	47(14)
	Wave-2	24 (4)	24 (3)	18 (4)	21 (6)
Home-start	Wave-1	10 (1)	11 (1)	5 (1)	1(0)
	Wave-2	6 (1)	2 (0)	4 (1)	1(0)
Home-end	Wave-1	34 (4)	41 (5)	13 (2)	36 (11)
	Wave-2	5 (1)	8 (1)	14 (3)	11 (3)
Added durations[1]	Wave-1	40 (5)	39 (5)	24 (5)	10 (3)
	Wave-2	25 (4)	22 (3)	6 (1)	14 (4)
Added departure Times[2]	Wave-1	8 (1)	9 (1)	6 (1)	3 (1)
	Wave-2	2 (0)	5 (1)	1 (0)	4 (1)
Added arrival Times[3]	Wave-1	5 (1)	0(0)	2 (0)	0 (0)
	Wave-2	2 (0)	2 (0)	1(0)	3 (1)

Percentage of reported trips is in parentheses.
(0) implies less than 0.5%;
[1] Trip durations were imputed using the estimated trip length and an assumed speed of 30 mph.
[2] Trip departure times were imputed by subtracting the estimated trip duration from the trip arrival time.
[3] Trip arrival times were imputed by adding the estimated trip duration to the trip departure time.

The augmentation of data files was necessary not only to recover as much information as possible for accurate and detailed assessment of changes in travel behavior, but also for the spatial and temporal analysis of travel patterns presented in this paper. A note is due here on the results obtained from the original (unaugmented) data files that have been disseminated earlier (e.g., Kitamura et al., 1990a, b). As the results presented later indicate, the basic findings in terms of the reduction in trip making and total distance traveled do not change after the augmentation.

The resulting trip file contains information on 2706 first wave trips and 2235 second wave trips made by the 219 stayers in 142 households. The "before-and-after" comparison of travel characteristics and the spatial and temporal analyses are performed on this data file.

A summary of the information retrieval achieved in both waves is shown in Table 6 for stayers by group membership. This summary can also be used to assess the reporting accuracy of the different groups. In general the telecommuter employees and control group employees along with the telecommuter household members showed very similar levels of augmentation. The employees were all participating in this project on a voluntary basis and the interest they had in the concept of telecommuting might have motivated their equally good reporting accuracy. The telecommuter household members who were directly affected by telecommuting may have been equally motivated as they experienced the benefits or disbenefits of telecommuting. The control group household members, on the other hand, showed a higher level of augmentation requirements, possibly because they had no motivating factor. In addition, we find that the levels of augmentation were higher in the first wave than in the second wave. This may be partially attributed to the updating of the panel survey instrument which provided an improved format in the second wave (Goulias et al. 1990). The augmentation resulted in an 8.3% and a 4.1% increase in the total number of trips analyzed in the first and second waves, respectively.

Analysis of travel characteristics

Table 7 shows a summary of the travel characteristics by group and wave. For the telecommuters, the second wave statistics are further divided by day type, i.e. telecommuting day and commuting day. Any travel characteristic in the second wave that is significantly different from that in the first wave (based on a paired t-test) at a 5% level is marked with an asterisk.

This tabulation of the augmented data file confirms the results reported earlier (Kitamura et al. 1990a, b). Telecommuters reduced their trips by about two trips on telecommuting days; the two trips presumably being

Table 7. Comparison of travel characteristics.

Travel Indicators	Wave	Telecom employees (73)	Control employees (65)	Telecom household (45)	Control household (36)
Trips/day	Wave 1	3.99	4.30	3.98	3.53
	Wave 2-TC	1.94*	n/a	n/a	n/a
	Wave 2-NTC	4.00	3.95	3.08*	3.30
Car trips/day	Wave 1	3.25	3.17	3.53	2.72
	Wave 2-TC	1.77*	n/a	n/a	n/a
	Wave 2-NTC	3.25	2.88	2.83	2.69
Work trips/day	Wave 1	1.02	1.10	0.74	0.60
	Wave 2-TC	0.09*	n/a	n/a	n/a
	Wave 2-NTC	1.11	1.07	0.70	0.77
Non-work trips/day	Wave 1	2.97	3.20	3.24	2.93
	Wave 2-TC	1.85*	n/a	n/a	n/a
	Wave 2-NTC	2.89	2.88	2.38*	2.53
AM peak-period trips/day	Wave 1	0.89	0.86	0.79	0.62
	Wave 2-TC	0.24*	n/a	n/a	n/a
	Wave 2-NTC	0.82	0.98	0.64*	0.50
PM peak-period trips/day	Wave 1	0.99	1.13	0.84	0.60
	Wave 2-TC	0.46*	n/a	n/a	n/a
	Wave 2-NTC	1.16	1.15	0.65	0.83
Avg distance/day (miles)	Wave 1	53.7	50.0	36.4	25.7
	Wave 2-TC	13.2*	n/a	n/a	n/a
	Wave 2-NTC	56.1	45.1	33.1	23.8
Freeway use/trip	Wave 1	53%	35%	31%	30%
	Wave 2-TC	10%*	n/a	n/a	n/a
	Wave 2-NTC	49%	40%	30%	25%
% Single stop Chains	Wave 1	55%	53%	47%	57%
	Wave 2-TC	75%*	n/a	n/a	n/a
	Wave 2-NTC	50%	51%	59%	43%

Notes: Wave 1: before telecommuting
Wave 2-TC: telecommuting day
Wave 2-NTC: non-telecommuting day
* Significantly different from wave-1 at a 5% significance level (as shown by a paired t-test).

those corresponding to the commute trips to and from work. This reduction in total trip making per day is statistically significant at the 5% level. The telecommuters made practically no work trips on telecommuting days. The average number of non-work trips (including return-home trips) is 1.85, which is significantly less than the first-wave counterpart of 2.97.

The most encouraging results are seen in car use and peak period travel. On telecommuting days, telecommuters made a significantly smaller number of total car trips and peak period trips. The notion that flexibility in task scheduling and the availability of free time increases car use does not seem to be supported by the data. Also, the drastic reduction in peak period travel suggests a possibly large impact that telecommuting could have on easing rush-hour traffic conditions. When given a choice, people choose not to travel during the peak period.

The total distance traveled per telecommuting day decreased by approximately 40 miles. Quite noteworthy is the fact that this corresponds to twice the home-to-work (commute) distance, which was found to be 19.5 x 2 = 39 miles. Telecommuters' savings in distance traveled is attributable to the elimination of the twice-daily commute. There is no increase in non-work travel on telecommuting days which offsets this savings; vehicle miles traveled for non-work purposes is about 13 miles whether the telecommuter commutes or not. The rather large reduction in travel distance suggests that telecommuting could significantly decrease gasoline consumption, at least in the short term.

The percentage of single stop chains (home based) increases from about 55% to 75%. Dividing the vehicle miles traveled by the total number of trips shows that average trip lengths are much shorter on telecommuting days than on commuting days (6.8 miles vs. 14 miles). These indications, coupled with the 40 percentage points reduction in freeway use suggest that, on telecommuting days, telecommuters make short, home-based trips that primarily involve surface street travel.

On average, 10% of a telecommuting day trip is spent on the freeway. This implies that, of the 6.8 miles, only 0.68 miles are on the freeway, while the remaining 6.12 miles are on surface streets. On commuting days, approximately 50% of a trip is spent on the freeway. The average 14 mile trip is then split equally with 7 miles both on the freeway and surface streets. This shows that, on average, there is a 90% reduction in freeway use with no increase in surface street travel. While this could have salutary effects on freeway congestion, the distribution of surface street travel needs to be probed. The higher percentage of home-based chains and the shorter trip lengths suggest that surface street travel is now more concentrated around residential locations. However, the total amount of surface street travel does not increase (7 miles on commuting days; 6.12 miles on telecommuting days).

The changes found in the telecommuters' travel patterns can be attributed to telecommuting only if the control group employees did not show equivalent changes in their travel patterns. The control group employees who commuted conventionally to work in both waves of the survey, did not show any statistically significant change in their travel characteristics, thus making it clear that telecommuting led to the changes observed in the telecommuters.

Despite their statistical insignificance, however, the reduction in trip characteristics shown by the control group employees was further investigated by the research team. A detailed analysis of the trip-reporting quality of control group members was performed to determine whether the reductions could be attributed to poor trip-reporting in the second wave. The results of this analysis are summarized in Pendyala et al. (1991).

The findings suggested that the control group employees' 8% reduction in trip making (from 4.30 to 3.95 trips per day) may be attributed to trip under-reporting in the second wave; but not with sufficient statistical evidence to conclude this. Moreover, there was no significant day-of-week effect to which variability in trip rates across the waves could be attributed. However, if the same level of trip under-reporting is assumed for telecommuters, their trip rates in the second wave would be 2.09 on a telecommuting day and 4.32 on a non-telecommuting day. Even under this assumption, it can be concluded that telecommuting substantially reduces trip generation. Evidence was also found to suggest that the household members of both telecommuters and control group employees under-reported trips in the second wave. Their travel characteristics presented in Table 7 need to be carefully interpreted with this in mind.

Spatial analysis

A spatial analysis of the impacts of telecommuting on travel patterns is essential in assessing its impact on energy, air quality, and land use. The spatial analysis presented in this section is a first step in which destination locations of non-work trips are examined. Figures 2 through 10 show the trip end distributions around home by group and by wave. The geocoded addresses of all non-work trip destinations are plotted such that their relative locations can be seen with respect to the home location, which is represented by the origin. Only non-work trip destinations are shown since work destinations are unlikely to be influenced by telecommuting. The X and Y axis give the coordinates in miles. The large circle in the middle of each graph is a 25 mile radius circle and gives an idea of the proportion of trip destinations that were chosen more than 25 miles away from home.

Figures 2, 3 and 4 show the trip destination distributions for telecommuters. The trip destination distribution for the first wave is shown in Fig. 2, while that for the second wave is shown in Figs 3 and 4 for telecommuting days and commuting days, respectively. A comparison of these three figures clearly shows that the trip destinations chosen on telecommuting days are very much closer to home than those chosen in the first wave. In the first wave, a

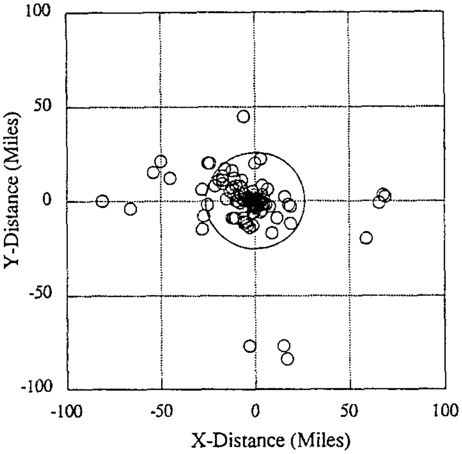

Fig. 2. Trip destination distribution around home for telecommuter employees: Wave-1 non-work trips.

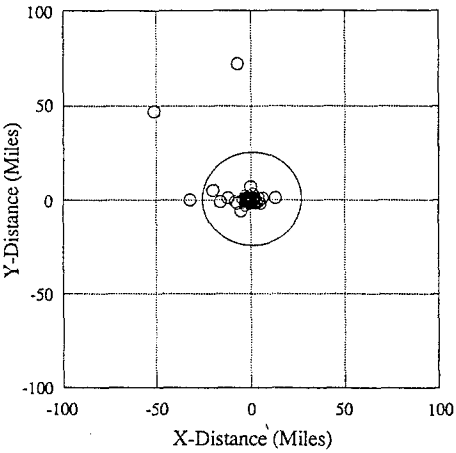

Fig. 3. Trip destination distribution around home for telecommuter employees on telecommuting days: Wave-2 non-work trips.

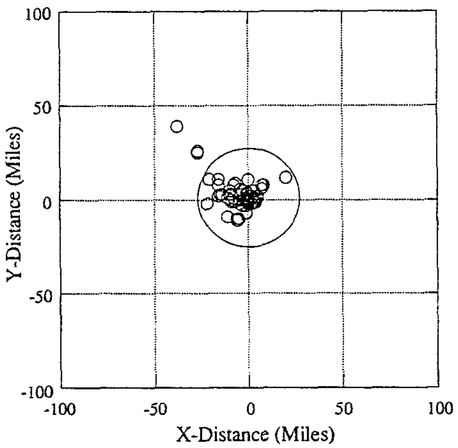

Fig. 4. Trip destination distribution around home for telecommuter employees on commuting days: Wave-2 non-work trips.

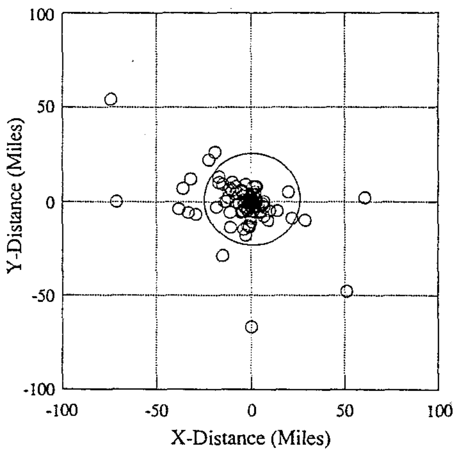

Fig. 5. Trip destination distribution around home for control group employees: Wave-1 non-work trips.

much larger number of trip destinations fall outside the 25 mile radius circle than on telecommuting days in the second wave. Even the spread of trip destinations within the 25 mile circle seems to be greater in the first wave.

In the previous section, it was found that telecommuter employees do not exhibit any change in distance traveled to non-work destinations (about 13 miles) between telecommuting and commuting days. The contraction in the spatial spread of non-work destinations then suggests that telecommuters are either performing different purposes on telecommuting days or substituting locations close to work with those close to home to perform the same purposes (or both). In either case, they do not want to spend more than 15 miles of travel on non-work activities, suggesting the presence of a travel time budget for non-work travel.

On second wave commuting days, the spatial spread of trips is certainly greater than that on telecommuting days with a larger proportion of destinations falling outside the 25 mile circle. However, it is important to note that the spatial spread is not as great as that in the first wave. The telecommuters are now choosing destinations closer to home even on commuting days. This is not an artifact of trip reporting errors because the control group employees do not show this difference between the waves, as shown in Figs 5 and 6.

Probing into this dramatic change in the telecommuters' action space is critically important for a better understanding of travel behavior as well as for an accurate assessment of the impact of telecommuting. It is possible that, as telecommuters get accustomed to traveling to closer destinations on telecommuting days, they and their household members go through a learning process during which they realize the benefits of choosing these destinations, such as savings in time and fuel. If this is so, then the telecommuter household would continue to use the same destinations on non-telecommuting days also and substitute farther destinations with closer ones. Another possible explanation is the household reallocation of tasks. As the telecommuters take over the household activities close to home on telecommuting days, they might continue performing these activities on commuting days also. Then, the household members would be taking over the household activities far away from home.

An examination of Figs 7 and 8 indicates no expansion in telecommuter household members' spatial spread of trip ends. In fact, there seem to be a slight contraction in the spatial spread of destinations chosen for non-work activities. This observation seems to corroborate the first of the two hypotheses stated above. There is no evidence of a household task reallocation in which telecommuters take over close-to-home activities and their household members take over the far-from-home activities. If this were true, we would have observed an expansion, rather than a contraction, in the spatial spread of

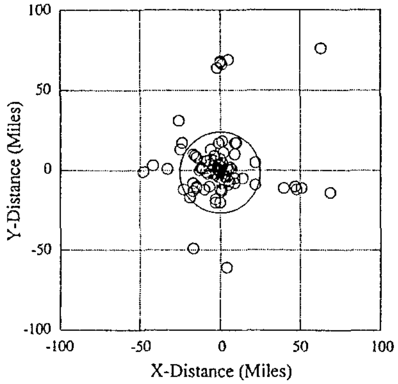

Fig. 6. Trip destination distribution around home for control group employees: Wave-2 non-work trips.

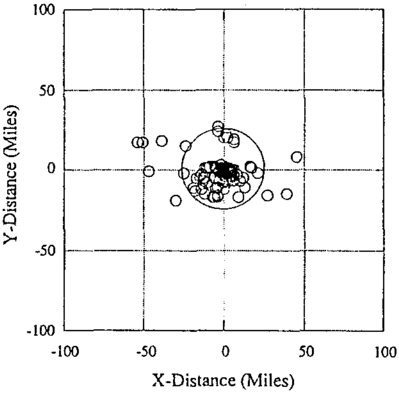

Fig. 7. Trip destination distribution around home for telecommuter household members: Wave-1 non-work trips.

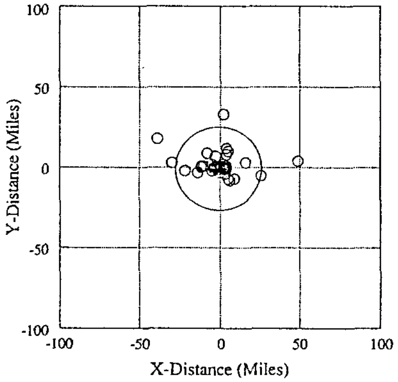

Fig. 8. Trip destination distribution around home for telecommuter household members: Wave-2 non-work trips.

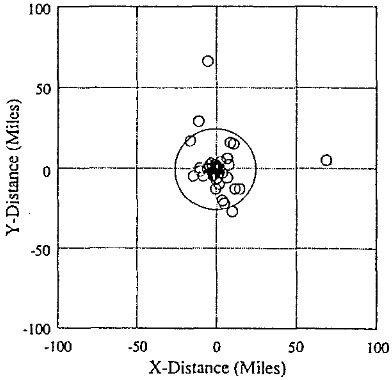

Fig. 9. Trip destination distribution around home for control group household members: Wave-1 non-work trips.

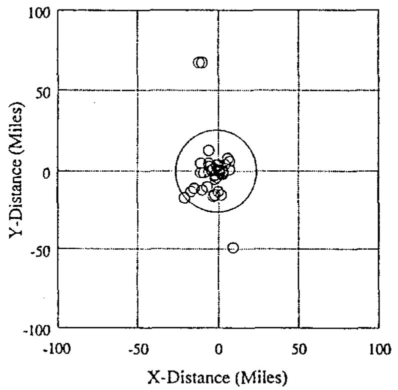

Fig. 10. Trip destination distribution around home for control group household members: Wave-2 non-work trips.

trip ends chosen by the telecommuter household members. A confirmatory analysis is necessary before the above conclusion can be drawn with certainty. A comparison of destination choices for different activities between the two waves for commuting and telecommuting days would provide further insights into the validity of the hypothesis.

The control group household members, similar to the control group employees, show no changes in the spatial spread of their destinations chosen across the two waves, as seen in Figs 9 and 10. Because of this, the differences in telecommuters' destination choice across the two waves can indeed be attributed to the introduction of telecommuting.

Table 8 shows a summary of the plots in terms of the frequency distribution of trip destinations by distance from home. Similar to the plots, the figures in the table represent percentages of trips made to non-work destinations. The first category corresponding to a zero distance from home represents the percentage of return-home trips. It is interesting to note that telecommuters are making the same percentage of return-home trips on both telecommuting days and commuting days. On average, about half of all non-work trips are home trips. This pattern persists whether or not the telecommuter is telecommuting. When the telecommuter telecommutes, he makes an average

Table 8. Distribution of trip destinations relative to home (excluding work trips).

Distance from home (X miles)	Wave	Telecom employees (73)	Control employees (65)	Telecom household (36)	Control household (45)
X=0 (home trips)	Wave 1	50%	49%	40%	51%
	Wave 2-TC	50%	n/a	n/a	n/a
	Wave 2-C	51%	43%	55%	56%
0<X≤12.5	Wave 1	35%	38%	47%	40%
	Wave 2-TC	46%	n/a	n/a	n/a
	Wave 2-C	42%	41%	40%	36%
12.5<X≤25	Wave 1	8%	7%	10%	6%
	Wave 2-TC	2%	n/a	n/a	n/a
	Wave 2-C	5%	8%	2%	6%
25<X≤50	Wave 1	2%	2%	3%	2%
	Wave 2-TC	0%	n/a	n/a	n/a
	Wave 2-C	1%	3%	3%	1%
X>50	Wave 1	5%	4%	0%	1%
	Wave 2-TC	2%	n/a	n/a	n/a
	Wave 2-C	1%	5%	0%	1%

Notes: Wave 1: Before Telecommuting
Wave 2–TC: Telecommuting Day; Wave 2–C: Commuting Day

of two trips (see Table 7), one of which is a return-home trip. This removes the opportunity to link trips because a multi-link chain would require making more than two trips. Therefore, the higher percentage of single-stop chains observed on telecommuting days (in Table 7) does not suggest that telecommuters reduce their trip-linking efficiency; it is simply a result of their reduced trip making and the reduced opportunities to link more than one out-of-home trip.

The Table also shows the contraction in spatial spread of destination choice on commuting days. In the second wave, 42% of trips are made within 12.5 miles, while the corresponding percentage in the first wave is only 35%. There is a noticeable reduction in percentage of destinations chosen more than 12.5 miles from home; 15% in the first wave versus 7% in the second wave. Similarly, the household members of telecommuters showed a contraction in their trip distribution patterns along with an increased percentage of return-home trips. There is quite a large reduction in their choices of destinations more than 12.5 miles from home; 13% in the first wave versus 5% in the second wave. All of these findings indicate a substantial reduction in the telecommuter households' action space.

Contingency table analyses were performed on Table 8 for each group to test the statistical significance of difference in trip destination choice

Table 9. Results of contingency table analyses on trip destination distributions.

Wave Comparison	Telecom employees		Control employees		Telecom household		Control household	
	Chi-sq	df	Chi-sq	df	Chi-sq	df	Chi-sq	df
Wave 1 vs. Wave 2-TC	13.4*	2	n/a		n/a		n/a	
Wave 1 vs. Wave 2-C	14.3*	2	5.0	2	20.9*	2	0.79	2
Wave 2-TC vs. Wave 2-C	4.89	2	n/a		n/a		n/a	

* Significant at a 5% level
Wave 2-TC: Telecommuting Day; Wave 2-C: Commuting Day
Note: The last three distance categories in Table 8 have been aggregated to avoid small expected cell frequencies.

across the waves. Despite the non-independent nature of the observations across the waves, contingency table analysis (applying Pearson's chi-square test) was used because it is conservative in rejecting a null hypothesis of equality of proportions. The results are summarized in Table 9. The results in Table 9 support the discussions presented earlier. The telecommuter employees and household members show significant differences in their trip destination distributions across the two waves, while the control group households do not.

It is noteworthy that telecommuter employees did not show a significant difference in their trip destination distributions between the telecommuting

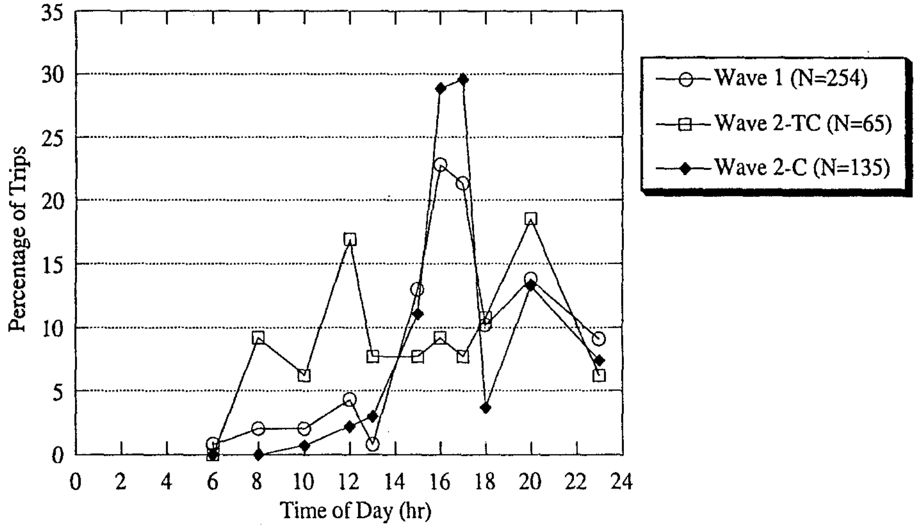

Fig. 11. Temporal distribution of home trips: Telecommuter employees.

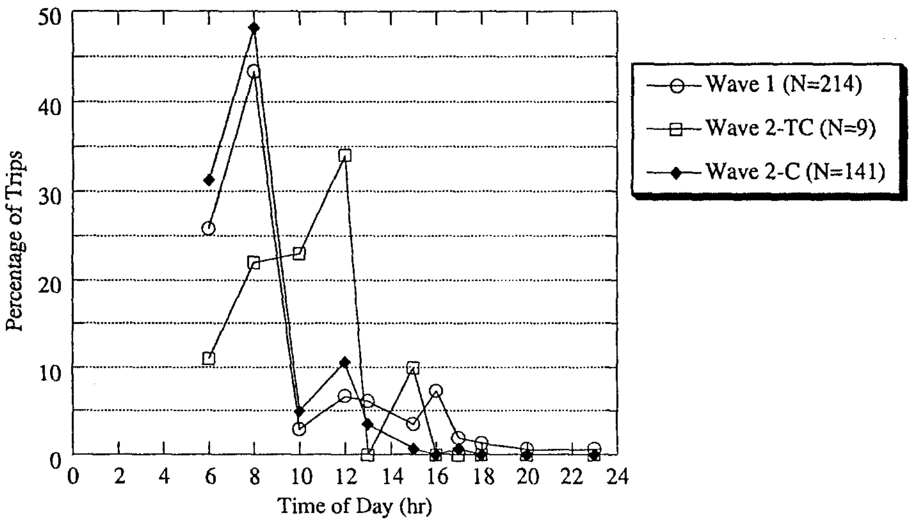

Fig. 12. Temporal distribution of work trips: Telecommuter employees.

and commuting days in the second wave. Non-work trip destinations chosen by telecommuters on commuting days are very similar to those chosen on telecommuting days. The hypothesis that telecommuter households go through an adjustment process in which they substitute farther destinations with closer ones is substantiated by the statistical analysis.

Temporal analysis

A temporal analysis of trip making involves the investigation of how and when various activities are allocated and performed during the day or over a longer period such as a week. This section provides distributions over a day of trip starting times to see how telecommuting impacted out-of-home activity engagement.

Figs. 11 through 16 show the distribution of trips by time of day. The percentage of trips by purpose (home, work, and non-work/non-home) is computed for each two hour time slot to obtain these figures. In Fig. 11, the distribution of home trips is shown for the telecommuter employees. Home trips are found to be very evenly spread out on telecommuting days when compared with other days, which could provide substantial relief to peak period traffic. On commuting days, the afternoon peak remains predominant both in the first and second waves. This probably corresponds to the return commute trip. However, it is interesting to see that the peak is

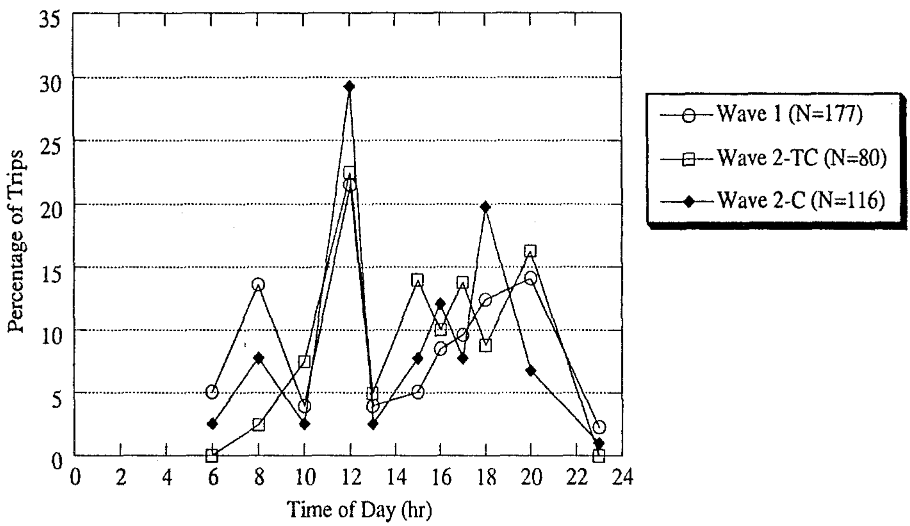

Fig. 13. Temporal distribution of non-work/non-home trips: Telecommuter employees.

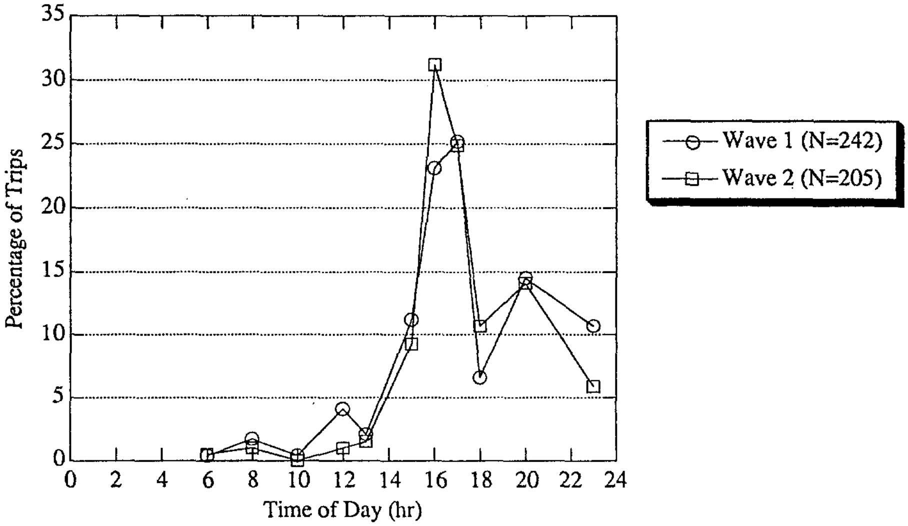

Fig. 14. Temporal distribution of home trips: Control group employees.

more concentrated on second-wave commuting days than on first-wave (by default) commuting days.

Fig. 12 shows the distribution of trips made to work by time of day. As expected the morning peak is predominant both in the first and second waves when the respondent is not telecommuting. The patterns are quite similar. The sample size of work trips is not large enough on telecommuting days to draw any meaningful conclusions. However, even among the few trips that were made to work, they were made in a more dispersed manner. This again shows the relief in peak period congestion that telecommuting can provide.

The distribution of trips made to non-work destinations (other than home) is shown in Fig. 13. These trips include shopping, personal business, recreation, eat meal, dental and medical, and any other trips. It is noteworthy that all the graphs follow the same general pattern. In general these trips appear to be made at the same times of the day both on telecommuting and commuting days. There is a peak during the lunch hour, while they tend to be pursued in the afternoon with no clear peaks. This pattern persists both in the first and second waves, whether or not the employee is telecommuting. This is indicative of a certain amount of habit persistence where the telecommuters tend to use the same hour of the day to make these trips. It is possible that these are eat-meal trips (lunch hour peak) and transport child trips which are not easily adjustable.

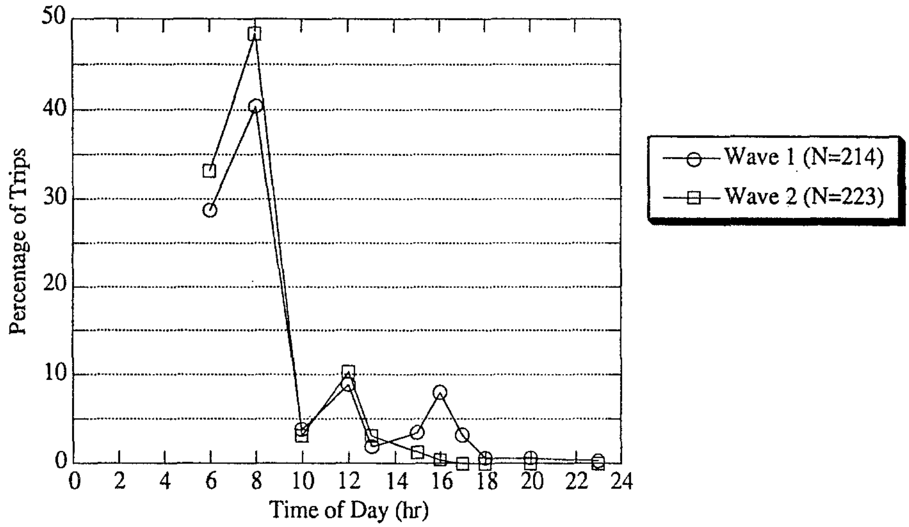

Fig. 15. Temporal distribution of work trips: Control group employees.

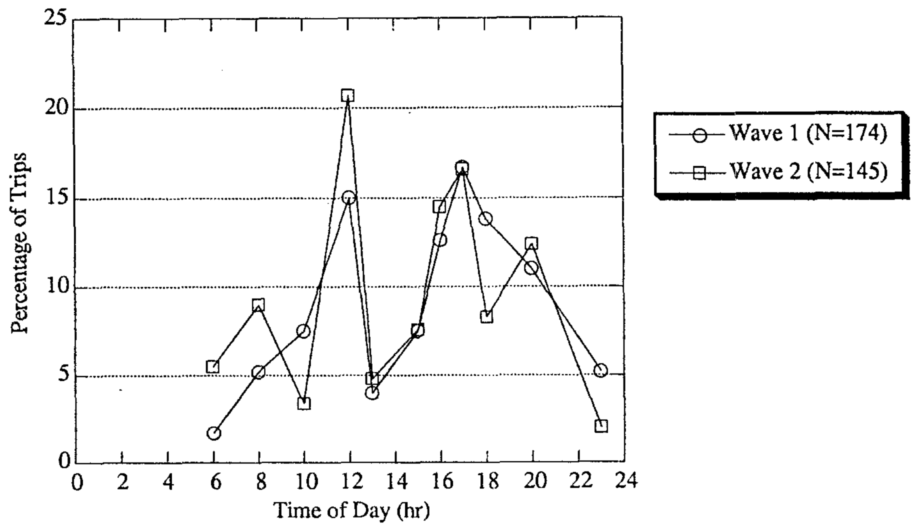

Fig. 16. Temporal distribution of non-work/non-home trips: Control group employees.

While the temporal patterns show this stability, the spatial analysis showed a significant difference in destination choice across the waves. In other words, it appears as though the non-work trips have been shifted in space, but not in time. In the first wave, they occurred close to work and involved substantial freeway use, while in the second wave, they occurred close to home reachable via surface streets.

The control group employees show similar patterns of trip distributions over the day between the first and second waves. Figs. 14 through 16 show the home, work and other trip distributions for control group employees in both waves. While the patterns are similar, there is a consistently higher peak in the second wave for all trip purposes. The home trips show a higher peak at about 5:00 pm, the work trips show a higher peak at about 7:00 am and the other trips show a higher peak at noon.

In order to assess the effects of telecommuting on peak period traffic, contingency table analyses were performed on the distribution of trip frequencies by time of day for each employee group. In the analysis, the day was divided into two categories – peak and off-peak periods; the former is defined as 7:00 am to 9:00 am and 4:00 pm to 6:00 pm while the latter represents the remaining hours of the day. Table 10 summarizes the results of the analyses.

Table 10. Results of contingency table analyses on peak vs. off-peak distribution of trips.

Trip purpose	Wave comparison	Telecom employees		Control employees	
		Chi-sq	df	Chi-sq	df
Home	Wave 1 vs. Wave 2-TC	26.80*	1	n/a	
	Wave 1 vs. Wave 2-C	6.77*	1	2.64	1
	Wave 2-TC vs. Wave 2-C	24.10*	1	n/a	
Work	Wave 1 vs. Wave 2-C	0.77	1	1.06	1
Non-work	Wave 1 vs. Wave 2-TC	1.06	1	n/a	
	Wave 1 vs. Wave 2-C	0.10	1	1.04	1
	Wave 2-TC vs. Wave 2-C	1.51	1	n/a	

* Significant at a 5% level
Wave 2-TC: Telecommuting Day; Wave 2-C: Commuting Day

The distribution of home trips between peak and off-peak periods is significantly different between the waves and is dependent upon whether or not the telecommuter is telecommuting. The difference between the first wave and the commuting days of the second wave is less pronounced, but still significant. The distributions of work and non-work trips show no significant differences between the waves. Also, the control group members showed very similar patterns across the waves. From this analysis, it seems that the relief in peak period congestion on telecommuting days comes only from the elimination of the two commute trips to and from work. The non-work trips show temporal stability and therefore do not contribute to any change in peak period trip making.

Conclusions

The spatial and temporal patterns of trip making before and after the introduction of telecommuting have been examined in this study in an effort to evaluate the impacts of telecommuting on the destination choice and activity engagement of telecommuter household members. Data obtained from a two-wave three-day panel travel diary survey conducted as part of the State of California Telecommuting Pilot Project in 1988 and 1989 provided the unique opportunity to perform this empirical analysis.

Trip-activity engagement profiles showing all details of trips and activities performed by an individual were developed in order to recover the maximum possible information from the travel diaries and impute any missing information that could be logically deduced. The geocoding of trip ends using the latitude and longitude of locations proved useful in performing a spatial analysis of destination choice.

It was found that the telecommuters significantly reduced their trip making and total distance traveled. A particularly encouraging result was the large reduction in peak-period trips and car trips. Trips made on telecommuting days were found to be shorter and involved less freeway use.

The spatial and temporal analysis presented in this paper is a first attempt at addressing long-run effects of telecommuting on fuel consumption, air pollutant emission, and suburban congestion. Telecommuters were found to have much reduced action spaces, i.e., spatial extension of activity locations. This pattern seemed to persist on both telecommuting and commuting days. The trip distribution patterns can be studied to assess the impact of telecommuting on suburban traffic conditions and land use development to gain an understanding of the long-term impacts of telecommuting on the urban environment. The results are also useful for identifying questions that need to be addressed in future research efforts, such as those dealing with the timing and duration of activities and trips.

The distribution of activities by time of day showed that telecommuter employees rescheduled and possibly reallocated their activities. Telecommuters spread out their home trips more evenly over the telecommuting day. They also showed higher and narrower home-trip peaks on commuting days. They showed no significant differences in the peak vs. off-peak distribution of work and non-work trips between the waves. The prevalence of non-work trips during the afternoon on telecommuting days suggests that activities performed in the afternoon are more binding (picking up children after school, etc.) or that the telecommuters had to get out of their home-office by force of habit. The relief in peak period congestion can therefore be expected only from the elimination of the two commute trips to and from work.

A note must be made regarding the limitations of this study arising from the selective nature of the sample. The sample consists of a small group of state government employees who volunteered to take part in the study. The small sample size coupled with the possible presence of selectivity bias should be considered before the results of this research are used for making transportation policy decisions.

The determination of the impacts of changes in destination choice and timing of trips on suburban congestion, air pollution and long-term land use development remains a challenging task. It calls for exploring and modeling the causal relationships existing among various factors influencing trip making, activity engagement and destination choice.

Acknowledgements

The authors are grateful to Patrick Conroy of the California State Department of Transportation for his encouragement and support during the research. Robert Short of the Maps Division at the California State Department of Transportation was particularly helpful in providing maps and assistance in geocoding. Thanks are due to Huichun Zhao at the University of California, Davis for his assistance in the preparation of the data. The services of Dickson Tam and Taki Kitamura in geocoding are greatly appreciated. Helpful suggestions were provided by Patricia L. Mokhtarian and Kenneth Kurani. Financial support provided by the University of California Transportation Center and the California State Department of Transportation is gratefully acknowledged.

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