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THE TRAVEL AND EMISSIONS IMPACTS OF TELECOMMUTING FOR THE STATE OF CALIFORNIA TELECOMMUTING PILOT PROJECT

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Abstract—The impacts of home-based telecommuting on travel behavior and personal vehicle emissions for participants in the State of California Telecommuting Pilot Project are analyzed using the most advanced emissions modeling tools currently available. A comparison of participants' telecommuting day travel behavior with their before-telecommuting behavior shows a 27% reduction in the number of personal vehicle trips, a 77% decrease in vehicle-miles traveled (VMT), and 39% (and 4%) decreases in the number of cold (and hot) engine starts. These decreases in travel translate into emissions reductions of: 48% for total organic gases (TOG), 64% for carbon monoxide (CO), 69% for nitrogen oxide (NOx), and 78% for particulate matter (PM). Although the authors developed the methodology to investigate the emissions impacts of telecommuting, the analysis technique can be applied to *any* demand management or other transportation strategy where all of the necessary model inputs are available. An analysis of the number of personal vehicle trips and VMT partitioned into commute-related and non-commute-related purposes revealed that non-commute personal vehicle trips *increased* by 0.5 trips per person-day on average, whereas the non-commute VMT *decreased* by 5.3 miles. This important finding supports (for one indicator, the number of trips) the hypothesis that non-commute travel generation is a potential negative impact of telecommuting. This finding demonstrates the need to monitor these changes as telecommuting moves into the mainstream. In this study, however, the small increase in non-commute trips has a negligible impact compared to the overall travel and emissions savings. Copyright © 1996 Elsevier Science Ltd

1. INTRODUCTION

In response to state and federal air quality regulations, transportation and air quality planners continue to evaluate and compare Transportation Demand Management (TDM) strategies designed to help alleviate regional air quality problems. A growing body of literature shows that telecommuting has positive travel-related impacts, including decreasing the number of vehicle trips and vehicle-miles traveled (VMT), especially during peak travel periods (Kitamura *et al.*, 1991; Hamer *et al.*, 1991; Pendyala *et al.*, 1991; Mokhtarian *et al.*, 1995). Home-based telecommuting shows particular promise as it entirely eliminates the need to commute to and from the main workplace. Whereas at least the short-term travel-related impacts of telecommuting are becoming clear, the emissions impacts are less certain. There are limits to the efficacy of using traditional transportation-related indicators (such as VMT, number of trips) to gauge the probable emissions impacts of various transportation strategies. These traditional measures only partially explain vehicle emissions. The vehicle emission process is very complex, involving the interaction of numerous other factors including: the vehicle types and pollution control technologies in the fleet; how the vehicles are operated (speeds, acceleration/deceleration, etc.); other travel-related indicators (such as number of cold and hot engine starts); and

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environmental conditions (including season and ambient temperature). Thus, to properly assess the emissions impacts of a transportation strategy, a vehicle emissions model that takes all of these factors into consideration must be used.

In 1991, the first known emissions analysis of telecommuting was performed using data from the State of California Telecommuting Pilot Project (Sampath *et al.*, 1991). Using travel diary data and an early version of the California Air Resources Board's (CARB) emissions inventory models, EMFAC7D / BURDEN7D, researchers at UC Davis were able to quantify the emissions impacts due to telecommuting. One important travel-related finding discovered during the research was that telecommuters traveled in closer proximity to the home on telecommuting days. However, a detailed investigation of the emissions impacts of this behavior was not performed at the time. Overall, the findings from the project supported the hypothesis that telecommuting has positive transportation and air quality impacts.

A later study on a different data set (the Puget Sound Telecommuting Demonstration Project) improved upon the State of California project by using a more thorough methodology and updated emissions models (Henderson *et al.*, 1996). The new methodology involved modifying the 7F versions of EMFAC and BURDEN to allow the replacement of *all* default aggregate data files in the models with sample-specific data, whereas only selected files were replaced in the earlier State of California analysis.

The present study seeks to re-evaluate and extend the State of California emissions analysis using the improved methodology and emissions models employed in the Puget Sound study as a starting point. In this study a true before-and-after comparison is conducted, whereas in the Puget Sound analysis travel and emissions are compared for non-telecommuting days and telecommuting days, irrespective of the time at which telecommuting began.

One issue of particular interest in this study is the previous observation that a higher proportion of trips occurred within a shorter distance from home on telecommuting days as compared to non-telecommuting days. The question is how this impact affects emissions levels. From a travel perspective, the observed result is an increased proportion of miles driven on slower surface streets rather than on freeways. The concern is that vehicles traveling at lower speeds do not perform under optimal combustion conditions, and thus produce running emissions at a higher rate. An important question then, is—in what way do lower average speeds impact overall emissions levels? This study addresses this issue in detail to determine what changes take place in travel behavior, what the impacts of those changes are on average trip speeds, and whether or not those impacts affect overall emissions levels.

Emissions estimates for this study are modeled with the latest versions of the CARB emissions inventory models, EMFAC7F and BURDEN7F. Data from the State of California pilot project are used to replace all aggregate input files in the models. A control group is used for comparison to determine the extent to which changes in travel behavior and emissions levels are actually due to telecommuting. Based on trips reported in a conventional travel diary format, the personal vehicle emissions of telecommuters (before and after telecommuting) and controls are compared to identify impacts due to telecommuting. Although the authors developed the methodology to investigate the emissions impacts of telecommuting, the analysis technique can be applied to *any* transportation strategy where all of the necessary model inputs are available.

The results reported here pertain to a summer analysis where ozone precursors (TOG and NOx) are of greatest concern. Summer was chosen to correspond with the earlier study of the same data to identify similar trends in the findings. The Puget Sound study focused on winter emissions estimates, and the reader should note that comparing emissions across seasons may show changes in emissions levels that are unrelated to vehicle activity.

It is important to note that the impacts on emissions levels reported here represent the difference between a day on which the telecommuter telecommuted and a day when the commute trip to the regular office was made. When the *level* of telecommuting is

considered, that is, the percentage of work days that employees actually telecommute, the weekly savings will be a much smaller proportion of total weekday travel. Also, these findings represent average per capita reductions; the aggregate (or overall, region-wide) impacts are determined by scaling these reductions by the number of program participants. Thus, the *aggregate effectiveness* of telecommuting must take into account the number of people likely to participate as telecommuters and how often they telecommute, not just the per capita, per occasion impacts.

The organization of this paper is as follows. Following this introduction (section 1), section 2 outlines the use of the travel diary data from the State of California Telecommuting Pilot Project participants in preparing for the emissions analysis. Section 3 describes methods of modeling mobile source emissions and presents the models used in this analysis, EMFAC7F and BURDEN7F, in detail. The travel-related and emissions findings are discussed in section 4, and finally, section 5 concludes with a summary of the study and recommendations for future research.

2. STATE OF CALIFORNIA DATA

The State of California Telecommuting Pilot Project began in 1988 as a two-year demonstration to test the effectiveness of telecommuting as an alternative work arrangement for employees of state government agencies (JALA Associates, 1990). The project was initiated due to the increasing costs of new office space, the changing nature of work at the state agencies, worsening congestion and air quality, and the need to conserve energy.

Three-day travel diaries were designed to collect data on the travel behavior of project participants. The participants in the study were state employees from 14 public agencies who volunteered to participate. Two travel diaries were completed by participants and driving age household members over the course of the study: one before each participant began telecommuting (Wave 1), and another after participants had been telecommuting for about one year (Wave 2). In the first wave all employees commuted conventionally to the main work place. In the second wave, the control group continued to commute conventionally, while the telecommuters were instructed to telecommute at least once during the three day travel diary period. Extensive evaluations of the impacts of telecommuting on travel behavior (Kitamura *et al.*, 1991) and preliminary evaluations of the impacts on vehicle emissions (Sampath *et al.*, 1991) were performed.

The State of California data is organized into two types of data files, a personal/household information file and a trip file. The personal and household information file includes information such as the participant status (telecommuter, control group member, telecommuter household member, or control group household member), age, gender, home and work locations, locations frequently visited, transit lines used and household car ownership. The trip files contain the trip characteristics for every trip reported by the respondents. The information for each trip includes the origin and destination, beginning and ending trip times, purpose, approximate trip length as reported by the respondent, mode used, beginning and ending odometer reading if a personal vehicle was used, the number of passengers and the percentage of distance traveled on the freeway for each trip. Detailed discussions of the State of California data are reported in Kitamura *et al.* (1991) and Pendyala *et al.* (1991). Also discussed are additional transportation findings, including an analysis at the household level.

The person and trip files formed the basis for this emissions analysis of telecommuting. The empirical findings reported here pertain to the analysis of 40 telecommuters (who reported travel in both waves with at least one telecommuting day in Wave 2) and 58 controls. This study focuses on the personal vehicle emissions impacts of telecommuting. Thus, carpool, vanpool and alternative transportation mode trips (e.g. bus, bike) were not included in this analysis. It is reasonable to assume that many if not most ridesharing trips would still have taken place without the telecommuter, and that telecommuting would have no emissions impacts on those trips. Also weekend data was not reported in the

Table 1. Distribution of trips across comparison group

	Telecommuters			Controls	
	Wave 1	Wave 2 TC days	Wave 2 NTC days	Wave 1	Wave 2
# of people	40	40	34	58	57
# of personal vehicle trips	429	142	212	572	490
# of person-days	114	52	56	161	149

travel diaries and therefore, non-work-day travel impacts could not be evaluated. Due to lower completeness and quality, household member data is also not analyzed. Thus, this study only addresses the emissions impacts of telecommuting for drive-alone trips on the project participants' work days.

As data cleaning efforts were being conducted, it was discovered that three participants were inappropriate for this study. Two of the participants telecommuted from a center rather than from home. The travel and emissions impacts of center-based telecommuting are likely to differ significantly from those of home-based telecommuting, and hence it is preferable not to combine those two groups. The third participant was an obvious outlier. For this person, two 50-mile commute trips were reported on days when the participant was supposedly telecommuting from home, and the participant did not report any non-telecommuting days (before or after telecommuting began) against which to compare for possible miscoding of the day status. With such a small sample, a single outlier can greatly skew the results. Therefore, that participant's trips were removed along with the trips made by the center-based telecommuters. Also, 31 of the 71 telecommuters originally studied did not report a telecommuting day in Wave 2, thus it is not clear if those participants ever actually telecommuted. Therefore, the telecommuter group sample size was reduced to 40 such that before and after measures were available for a consistent set of participants. The reduced sample size means that the travel related findings of this study and the previous studies of the same data are not quantitatively comparable. Qualitatively, however, the key findings can be compared for these studies and in fact are consistent.

Table 1 shows the trip tabulations from the 40 telecommuters and 58 controls analyzed in this study. The trip data from the participants were divided into five groups: (1) Telecommuters, Wave 1 (before telecommuting); (2) Telecommuters, Wave 2 (after starting to telecommute, on telecommuting days); (3) Telecommuters, Wave 2 (after starting to telecommute, on non-telecommuting days); (4) Controls, Wave 1, and (5) Controls, Wave 2. The total number of personal vehicle trips taken by telecommuters and controls in Wave 1 were 429 and 572, respectively. In Wave 2, telecommuters took 354 total trips, 142 on telecommuting days (TC Days) and 212 on non-telecommuting days (NTC Days). The controls reported 490 trips in Wave 2. The third row in the table represents the total number of person days for each group. In this context, a person-day is defined as a day on which a participant in the study kept a record of his or her trips.

3. MODELING MOBILE SOURCE EMISSIONS

Generally speaking, the current strategy for modeling vehicle emissions involves two steps. First, emissions factors (e.g. g/cold start, g/mile of emissions) are developed for each emissions-producing vehicle activity (e.g. cold engine starts, VMT). Second, the emissions factors are multiplied by the appropriate vehicle activity to generate total emissions for that activity. Modeling emissions using this two step process is inherently data-intensive. The main data requirements for vehicle emissions modeling include the following (Guensler et al., 1994): (1) quantifying the emissions-producing vehicle activity (e.g. cold vehicle starts, hot vehicle starts, number of trips, VMT); (2) identifying the characteristics

of the vehicle fleet, including vehicle model years, vehicle classes, operating characteristics, and pollution control technologies; (3) providing data on environmental factors (e.g. season, altitude, ambient temperature); and (4) collecting emissions factor data for each emissions-producing process (engine starts, running exhaust processes, and evaporative processes). Computer emission models then use these data to calculate a total emissions inventory by weighting each emission-producing activity by its appropriate emissions factor and summing the totals for all activity in the sample.

3.1. Overview of EMFAC and BURDEN

The California Air Resources Board's emissions inventory models, EMFAC7F and BURDEN7F, are used to calculate the emissions estimates for this analysis. As generally employed, these models use the basic methodology described above to calculate aggregate vehicle emissions inventories for air basins in California (CARB, 1993). Seven **pollutant types** are modeled by EMFAC7F and BURDEN7F: total organic gases (TOG), reactive organic gases (ROG), carbon monoxide (CO), nitrogen oxides (NOx), sulfur oxides (SOx), particulate matter (PM), and lead. The SOx and lead outputs are not presented here because the vehicle activity in this small sample did not generate measurable amounts of these pollutants. Also, since ROG is a subset of TOG it is not presented separately. The input requirements for BURDEN7F demanded that personal vehicles be classified into **class/technology groups**. Four categories of vehicles were present in this sample: a light duty automobile (LDA) class subdivided into catalyst-equipped and non-catalyst-equipped technology groups, and a light duty truck (LDT) class with the same two sub-categories. Though the sample did include five trips made on motorcycles, to simplify the analysis these trips were conservatively classified as LDA trips with the same year vehicle. Vehicles are modeled as having seven different **emission-producing processes**: running exhaust, cold start exhaust, hot start exhaust, hot soak emissions, evaporative running losses, diurnal emissions, and evaporative resting losses. To include the impacts of changing ambient temperatures on vehicle emissions, BURDEN7F models personal vehicle emissions for six different **time periods** throughout the day. The time periods are: 12 midnight–6 a.m., 6–9 a.m., 9 a.m.–12 noon, 12 noon–3 p.m., 3–6 p.m., and 6 p.m.–12 midnight.

For a particular calendar year and season (specified by the user), EMFAC7F calculates an array of emissions factors for each combination of vehicle class/technology group, emissions process, and pollutant type. BURDEN7F references these emissions factors, and compiles the emissions inventory for a specific set of vehicle activity data for each of the six time periods of the day. The emissions inventory is produced by weighting each measure of vehicle activity (VMT, number of cold starts, etc.) with the appropriate emissions factor and summing these emissions figures for each time period of the day. Data is then reported in terms of average emissions per day for a particular calendar year. For an in-depth discussion of the models and sample formats of input and output files, refer to CARB (1993).

3.2. Uncertainty in modeling vehicular emissions

Several researchers (e.g. Pierson et al., 1990; Pollack et al., 1992) have found that the emissions estimates from models (such as EMFAC/BURDEN and the federal EPA model, MOBILE) are lower than field-measured pollutant concentrations. These studies have raised concerns about the accuracy and usefulness of the models. A lack of detailed data on the emissions-producing processes necessitates that simplifying assumptions be made to replicate these processes using empirical equations in computer models. Further, because the models were developed as tools to estimate emissions for large geographical areas, aggregate regional data is typically used for inputs.

Additional challenges arise when using regional emissions inventory models for small-scale studies such as this. To model emissions for a small-scale analysis, at the very least the vehicle activity data specific to the sample must be input to the models. Other default data files (fleet mix, speed distribution, etc.) should also be replaced for more comprehensive analyses.

While we are cognizant of the shortcomings of current emissions models, we maintain that with the appropriate input data they can be very useful tools for providing a relative comparison of emissions levels among groups. The EMFAC7F and BURDEN7F models used in this study are among the most advanced mobile source emissions models available and represent the current state of the art. Because of the potential for modeling inaccuracy, however, the specific emissions figures provided in this report (in g/day) should be used with caution. The percent differences among groups should be a more reliable measure and is the primary basis for comparison presented here. Several steps were taken in this study to decrease the potential for error in the emissions estimates. These are discussed in detail below.

3.3. Modeling improvements made for this analysis

One potential cause of modeling error is the use of aggregate input data. In this small-scale analysis this error is eliminated by replacing the default aggregate input files with more accurate sample-specific data. To develop the inputs for this study, the travel diary data from the participants in the State of California project were coded, cleaned and tabulated for input to EMFAC7F and BURDEN7F. The data were tabulated to fulfill all of the main data requirements for the models — vehicle activity, fleet mix characteristics, and environmental data. In the original State of California analysis aggregate vehicle fleet and speed distribution data files were used. In this new analysis, *all* aggregate input files are replaced with sample-specific data from the State of California project participants. Each of the improvements made is discussed below.

First, the default California vehicle fleet mix was replaced with the actual vehicle profile of the participants in the project. The default California fleet mix used in the original emissions analysis is not representative of the vehicles owned and driven by the participants in the demonstration project, since the sample has a higher proportion of later model year vehicles. For example, 1980 and earlier model year vehicles comprise 24% of the default fleet compared to only 13% of the demonstration project vehicle fleet.

Vehicle speeds are important as they affect the rate (in g/mile) at which pollution is emitted by a vehicle. The speed distribution profile in BURDEN is used to determine which emission factors to multiply against the measures of vehicle activity to generate the emissions output. All model runs were performed using the actual speed distribution data from the demonstration project instead of the default Sacramento county vehicle speed profile used in the original analysis.

Finally, since the original State of California evaluation in 1991, the California ARB released a new (7F) version of EMFAC and BURDEN. The improvements to the empirical equations in the current version improved the accuracy of predicted emissions levels, making them closer to field-measured pollutant concentrations. In comparison to the previously reported findings, this generally upward correction to estimated emissions will counteract to some degree the downward correction obtained by using the sample-specific fleet mix (containing a higher proportion of newer, lower-emitting vehicles than the default). Overall, the use of these improved versions of EMFAC and BURDEN in conjunction with the changes described above should lead to more accurate emissions results for this study.

3.4. Factors affecting the emissions impacts of telecommuting

Air quality may be affected in three different ways as a result of telecommuting. *Direct transportation* impacts are those first-order effects on the participants' travel patterns that are observable from the travel diary data in isolation. *Indirect transportation* impacts include higher order changes such as effects on household travel, weekend travel, and long-term residential relocation. *Indirect non-transportation* impacts related to energy consumption changes should also be considered in a complete analysis of the air quality impacts of telecommuting. For example, utility consumption may grow if there is an increased use of heating or air conditioning at the remote work site while utility con-

Table 2. Primary emission-producing vehicle activities and emissions produced

Emission-producing vehicle activity	Type of process (pollutant)
Vehicle-miles traveled	● Running exhaust (CO, TOG, NOx, PM) ● Running evaporative emissions (TOG)
Engine starts (hot and cold)	● Start-up exhaust (CO, TOG, NOx, PM)
Engine shut-downs	● Hot soak evaporative emissions (TOG)
Modal behavior (e.g. accelerations, decelerations, average speeds)	● Running exhaust (CO, TOG, NOx, PM)
Park time	● Resting evaporative emissions (TOG) ● Diurnal emissions (TOG)

Adapted from Guensler, 1993

sumption at the main office is relatively unaffected. Here, the available data permit only the direct transportation impacts of telecommuting to be studied.

Telecommuting has the potential to reduce mobile source emissions levels by decreasing the types of vehicle activities which produce emissions. Table 2 shows the primary emissions-producing activities from automobile use that are typically included in the emissions inventory modeling process. Next we discuss which of these factors can be influenced by telecommuting and how these changes will affect vehicle emissions levels.

3.4.1. Vehicle-miles traveled (VMT). The amount of VMT directly affects running exhaust and running evaporative emissions. Running emissions are a significant contributor to all pollutants (TOG, CO, NOx, and PM), constituting more than 50% of the total emissions for NOx and PM. Telecommuting from home eliminates the need to commute to and from work. If additional trips aren't made on telecommuting days (as several studies have shown), telecommuting will cause significant decreases in total VMT. Ultimately, decreases in VMT due to telecommuting will result in lower vehicle emissions for all pollutants, especially NOx and PM.

3.4.2. Engine starts (cold and hot). Engine starts are directly related to the total number of personal vehicle trips. Engine starts cause elevated exhaust emission rates for the first few minutes of operation. Cold start emissions are greater than hot start emissions by an order of magnitude, and thus are a major concern. They are the primary source of CO and TOG emissions for short-to-moderate length trips. By eliminating the commute trip, telecommuting has the potential to decrease the number of total trips taken on a daily basis. If telecommuting decreases the number of personal vehicle trips (especially cold start trips) significant decreases in CO and TOG will result.

3.4.3. Engine shut-downs (hot soaks). When a vehicle engine is turned off, coolant stops circulating and engine temperatures rise resulting in increased evaporative (TOG) losses from the fuel system. Hot soak emissions, as they are called, are therefore also a direct function of the total number of trips taken. To the extent that telecommuting decreases the number of vehicle trips, reductions in hot soak (TOG) emissions are expected.

3.4.4. Modal behavior. Modal behavior, or an individual's driving pattern (such as acceleration rates, deceleration rates, and average speeds), greatly influences vehicle emissions rates. In general, for low to moderate speeds, there is an inverse relationship between speed and running emissions rates (CARB, 1990). Higher speeds mean lower emissions rates up to approx. 55 mph for TOG and CO (50 mph for NOx), beyond which higher speeds lead to higher emissions rates. Particularly for TOG and CO, the largest variations occur at low speeds. For moderate speeds, i.e. 20–55 mph (50 for NOx) the emissions rates decrease slowly. Therefore, if trip speeds shift by only a few miles per hour, but remain in this range, the impacts will be small. However, if speeds are shifted into or out of this range, as a result of telecommuting, significant emissions impacts may

result. The likely impacts of telecommuting on travel speeds are ambiguous—other things being equal, higher travel speeds will occur if more trips are made at off-peak (uncongested) times of the day. Alternatively, lower speeds are likely if trips are shifted from the freeways to the surface streets, where vehicle travel is typically slower (Sampath *et al.*, 1991). Acceleration/deceleration patterns are influenced by telecommuting to the extent that trips are shifted out of congested stop-and-go traffic into more free-flowing traffic in the off-peak period. The data used for this study do not allow accelerations and decelerations to be determined; only the average speed for the trip can be calculated from distance and time. While EMFAC7F and BURDEN7F do not model the emissions impacts due to acceleration and deceleration in detail, the Federal Test Procedures (FTPs) used to determine the baseline emissions factors contained in EMFAC7F do include standardized acceleration/deceleration test cycles, so these impacts on emissions are modeled to some extent. Average trip speeds are available, however, and are used to replace the default aggregate data to improve the modeling accuracy.

3.4.5. Park time (exposure to diurnal temperature fluctuations).   Evaporative (TOG) losses occur even when a vehicle is parked. Diurnal emissions are the evaporative emissions from a vehicle's fuel system which are caused by fluctuations in daily ambient temperature experienced by a parked vehicle. This loss also occurs while the vehicle is being operated, but is included within running evaporative emissions during that activity. To the extent that telecommuting decreases vehicle usage (thereby increasing the time a vehicle spends parked), increases in diurnal (TOG) emissions will be reported in the model output with corresponding decreases in running evaporative emissions. The overall amount of evaporative emissions from the vehicles' fuel systems due to diurnal temperature fluctuations will essentially be constant, and will be unaffected by telecommuting.

There are conditions, however, when telecommuting may increase the diurnal emissions. When a vehicle is parked longer than a day or two, the evaporative emissions control (the charcoal canister) can become saturated, and lose its effectiveness until the engine is run and the system purged of its collected vapor. The length of time to saturate depends on whether re-formulated fuel is used (which lowers the evaporation rate for a given set of conditions), whether the vehicle is parked in the sun or not, and so on. To the extent that telecommuting results in a vehicle not being driven for more than a day, the *multi-day* diurnal emissions can increase. Although the data for this study did not allow days to be identified on which no trips were made with a personal vehicle (see section 3.5), these days do in fact occur. The Puget Sound study previously referenced showed that on 38% of the participants' telecommuting days no trips were made (by the telecommuter) with a personal vehicle. Even if those days could be identified here, analyzing multi-day diurnal emissions would require data for several consecutive days, and would necessitate the tracking of all trips made by each vehicle, rather than just the trips made by the telecommuter. Further, the emissions factors calculated by the EMFAC model are based on aggregate measures that are not sensitive to individual vehicle activity. Therefore, variables affecting multi-day diurnal emissions cannot be modified by the analyst. Based on these restrictions, such an analysis is beyond the scope of this study. However, in any case, the increase in average emissions resulting from these occurrences is expected to be negligible compared to the magnitudes of the overall levels from the other processes.

3.4.6. Other factors affecting emissions levels.   The season in which the vehicle activity takes place and the ambient temperature directly affect the rates at which emissions are produced. Changes in temperature and Reid vapor pressure cause changes in emissions rates of every process. For example, cold start emissions are very sensitive to ambient temperature. In general, cold start emissions increase as ambient temperature drops. Thus, if telecommuting causes a shift in trips to times of the day when temperatures are higher, substantial reductions in cold start emissions could be realized.

Still other factors affect the total *air quality* impacts of telecommuting. For example, the topography of a region, the existence of a temperature inversion layer and wind patterns

all influence the rate of pollutant dispersion. These other factors can be simulated using pollutant dispersion models. However, because the focus here is solely on the *production* of vehicle pollutants, an analysis of the natural dispersion of emissions is beyond the scope of this study.

3.5. Calculating emissions impacts

To calculate the emissions impacts of telecommuting the emissions output from each group was converted to g/person/day, or g/person-day, to control for the different size groups.

While calculating the g/person-day for most of the comparison groups was straight-forward, doing so for telecommuters' Wave 2 on TC days proved to be more difficult. Because the participants in the sample are home-based telecommuters it is expected that there will be some days on which they telecommute from home and make no personal vehicle trips. These days should be included in the denominator of the g/person-day calculation, as the reduction of personal vehicle travel due to telecommuting is precisely one of the impacts we are attempting to measure. However, this data was unavailable from the State of California data files due to a flaw in the travel diary design. The travel diary did not provide a place for respondents to mark that no trips were made on a par-ticular day. Hence, it was impossible for the data coders to tell if a diary day with no data was the result of the respondent failing to document trips that were made or if it was simply a day on which no trips were taken. Rather than attempting to include estimates of the number of days on which no trips were made, the authors took the conservative approach of using only the data directly reported. It is important to point out that days on which no trips were taken can have significant impacts on the emissions reductions and should be included in future studies whenever possible. By not including these days, the emissions reductions due to telecommuting are underestimated. For example, in the Puget Sound study (Henderson *et al.*, 1996), no personal vehicle trips were made by tele-commuters on a sizeable 38% of all telecommuting days.

4. FINDINGS

This section begins with an analysis of the telecommuters and the controls in the sample to determine the usefulness of the controls as a comparison group. This is followed by a presentation of the transportation-related findings from each of the groups studied. An analysis of the emissions impacts is then presented, followed by an investigation of how VMT and speed distributions change as a result of telecommuting and what the transportation and air quality impacts of those changes are. Finally, the Distance to Cold Start Ratio (D/C Ratio) is calculated and discussed.

4.1. Comparability of telecommuters and controls

The control group in the study provides a sample against which to compare the tele-commuters. Before assessing the changes in travel and emissions due to telecommuting, it is important to check the extent to which the telecommuters and controls are comparable, independent of telecommuting. In the following discussion, all variables are in units of number of occurrences per person-day. Comparing the travel-related indicators of the two groups in Wave 1 (Table 3) shows that the telecommuters and controls in the sample take approximately the same average number of personal vehicle trips per day (3.8 and 3.6, respectively), with no statistical difference. Similarly, the average numbers of cold and hot starts show no significant differences between groups. However, the telecommuters have a higher VMT (44.8 miles) than the controls (32.7 miles), a (statistically significant) 37% difference. Based on the above observations, the control group was anticipated to provide a useful comparison measure for at least three of the four travel indicators: number of trips, cold starts, and hot starts.

To further analyze this significant difference in VMT, average commute lengths for the two groups were compared. The commute lengths were calculated only for those

Table 3. Comparing the Wave 1 travel characteristics of telecommuters and controls

	Telecommuters *Wave 1* # people = 40 # person-days = 114	Controls *Wave 1* # people = 58 # person-days = 161	% Difference between telecommuters and controls
VMT	44.8	32.7	37*
# of vehicle trips	3.76	3.55	6
# of cold starts	2.52	2.49	1
# of hot starts	1.24	1.06	17

* Difference in means is statistically significant at $P \leqslant 0.01$

participants who reported at least one trip that started at home and ended at work, or vice versa. Some participants did not drive straight from home to work within the travel diary period, so accurate commute lengths were unavailable for those participants. Based on 40 control group members and 34 telecommuting group members, the control group members have a longer average commute length (37.2 miles round-trip) than the 33.9 mile average commute for the telecommuters. This suggests that since telecommuters have a higher daily VMT, they must have more non-commute travel (in terms of total distance, not number of trips) than the controls. However, it should be noted that, in general, the average commute length is not equal to the average daily commute VMT, since the VMT depends on the frequency with which the commute trip is made in the sample. This point is explored in greater detail for the telecommuters in Section 4.3.

4.2. Travel-related findings

Four travel-related indicators were analyzed: VMT, number of vehicle trips, number of cold starts, and number of hot starts. Analysis of variance (ANOVA) was conducted for each of these indicators. Three effects were analyzed: the person effect, the wave effect,
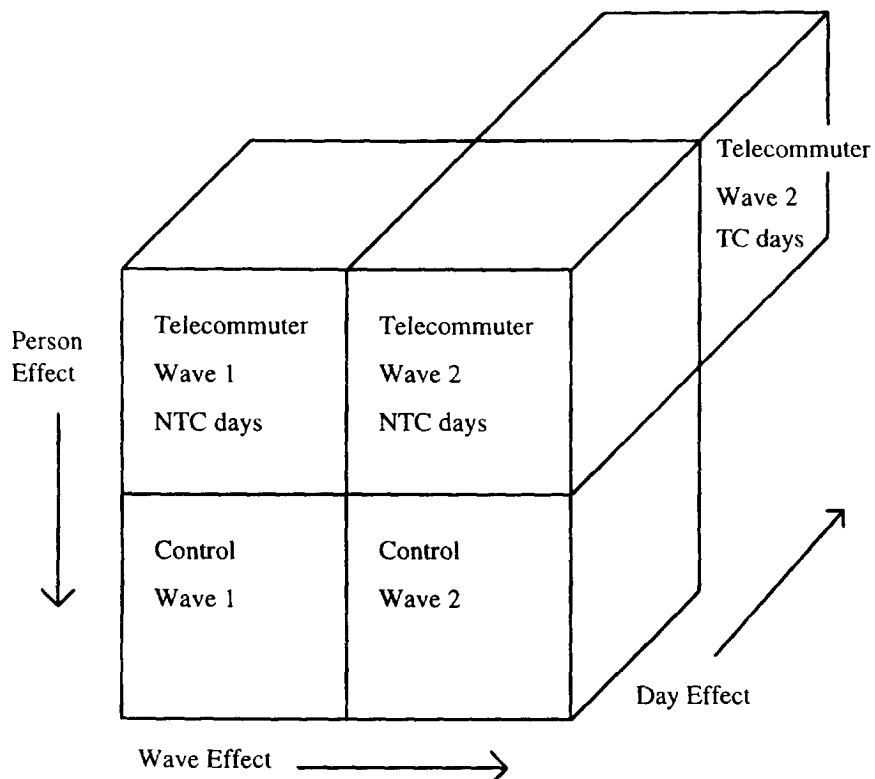

Fig. 1. Structure of ANOVA comparison groups.

and the day effect. The person effect compares the telecommuter sample and the control sample to determine if they are statistically similar. For dependent variables (travel indicators) that do not show significant differences between groups, the telecommuter and control groups can be pooled to provide a larger sample for more robust results. Similarly, the wave effect weighs the differences between the before and after measures with the same goal: to pool samples and increase robustness. Finally, the day status effect only applies to the telecommuter Wave 2 participants. This effect is characterized by the telecommuting day or non-telecommuting day status.

The ANOVA structure is displayed in Fig. 1 to assist in visualizing the relationship among the five groups. Because a full $2 \times 2 \times 2$ design is not possible (since the day status effect only applies to one of the groups), a three-way ANOVA could not be conducted. Instead, a two-stage analysis was performed. In the first stage, a two-way ANOVA, testing for person and wave effects, was conducted on the four groups forming the front surface of Fig. 1. In some cases, the assumption of equal variances across groups (required for ANOVA to be legitimate) was violated. However, the ANOVA results were not used directly, but rather to suggest the appropriateness of pooling two or more of the four groups for comparison against the fifth group in the second stage. In the second stage, t-tests were performed on the mean differences between the pooled non-telecommuting day group and the telecommuting day group. The t-test formula for either equal variances or unequal variances was used as appropriate. Hence, the second stage test is an entirely rigorous one. This approach was considered superior to the brute force approach of conducting pairwise t-tests of the telecommuting day group against each of the other four groups, which would have increased the likelihood of at some point falsely rejecting the null hypothesis of no significant difference between groups.

In the first stage, the two-way ANOVA revealed that for all four variables, neither the wave main effect nor the interaction effect was significant. For three of the four variables the person status main effect was also insignificant. Not surprisingly, however, the person status main effect was significant for VMT.

Since three of the dependent variables showed no significant differences due to the person and wave effects, for those three variables all four groups were pooled to provide the most robust comparison against the telecommuting day group in determination of the day status effect. In the second stage, a t-test was performed to compare the four pooled groups to the telecommuting day group to determine differences in the number of trips, the number of cold starts, and the number of hot starts. Since the person status was significant for the other variable (VMT), only the telecommuter before and after (NTC day) groups were pooled for comparison. The results of this second stage are presented in Table 4 and show that three of the four indicators changed significantly as a result of the day status effect. Only changes in the number of hot starts were found to be insignificant.

An interesting observation can be made by combining the results of both stages. The wave effect was insignificant for all four dependent variables (a stage 1 result). This means

Table 4. Travel impacts of telecommuting (per person-day)

	Telecommuters			Controls		
	(1) W1 40 people 114 days	(2) W2 TC 40 people 52 days	(3) W2 NTC 34 people 56 days	(4) W1 58 people 161 days	(5) W2 57 people 149 days	(6) Pooled sample
VMT	44.8	10.2*	36.9	32.7	31.1	42.3[1]
# of trips	3.76	2.73*	3.79	3.55	3.29	3.55[2]
# cold starts	2.52	1.54*	2.61	2.49	2.20	2.44[2]
# hot starts	1.24	1.19**	1.18	1.06	1.09	1.10[2]

[1]Pooling telecommuters' W1 and W2 NTC days: 40 people, 170 days
[2]Pooling all 4 NTC day groups: 98 people, 480 days
* Difference is statistically significant from columns 1 and 6 at $P \leqslant 0.001$
** Difference is not statistically significant from columns 1 and 6

that telecommuting significantly decreased three of the four measures on telecommuting days (a stage 2 result), while leaving non-telecommuting day travel unaffected.

The effects of telecommuting shown in Table 4 are discussed in two ways. First, the telecommuters' Wave 1 days are compared to their Wave 2 TC days (columns 1 and 2) to illustrate the impacts of telecommuting on that particular group of people. Second, the pooled samples are compared to the telecommuters' Wave 2 TC days (columns 6 and 2) to incorporate a more robust estimate of the influence of other factors that may have impacted all groups between the first and second waves.

Comparing telecommuters' Wave 1 to their Wave 2 (on TC Days) shows that telecommuting caused large reductions in the personal vehicle (PV) travel of project participants. After telecommuting began telecommuters took one fewer drive alone trips per day on average than they did in Wave 1 (a 27% decrease). This reduction in the number of trips translated to a 39% decrease in cold starts, and a 4% decrease in hot starts. Average VMT also decreased by a substantial amount (77%), from 44.8 miles before telecommuting to 10.2 miles on telecommuting days.

The 77% savings in VMT for this particular sample of telecommuters is larger than would be expected from a more representative sample since their average (round trip) commute is longer than the regional average. Though the regional average commute length figure for drive-alone trips was not available for direct comparison, studies of the same data for all modes of transportation showed that this sample of telecommuters, on average, comprises long distance commuters (Mokhtarian *et al.*, 1995). As telecommuting becomes more widespread, commute lengths of telecommuters are expected to fall closer to the regional average and the VMT reductions are expected to decrease.

Comparing the pooled groups to the Wave 2 telecommuting day group shows very similar results. The number of PV trips was reduced by 23% from 3.55 trips per day to 2.73. The number of cold starts decreased by 37%, while the number of hot starts increased by 8%. The change in the number of hot starts is statistically insignificant ($P = 0.719$). The small differences in hot starts can be considered noise about a nominal change roughly equal to zero. VMT reductions were 76% when compared to the pooled group. These similar results indicate that the changes in travel behavior did not depend heavily on factors other than telecommuting.

A question of interest is why the number of cold starts decreases significantly while the number of hot starts remains unchanged. The reason is that the early morning commute (and cold start) were eliminated for most of the participants on telecommuting days. This effect can be observed by referring to Fig. 4 (found in section 4.6). Although the figure is used to display a VMT result, it is the case that during times of the day when VMT was very low, the number of trips was low as well. This accounts for the reduction of a single cold start (observed in Table 4). The afternoon chain of trips began with a cold start whether that chain contained a commute trip or not. Since the reduction in the number of trips was also roughly equal to one, it was the single cold start trip that was eliminated, while hot starts remain unchanged.

4.3. Impacts on non-commute travel

A detailed analysis of telecommuters' Wave 1 (Table 4, column 1) and Wave 2 TC day (Table 4, column 2) travel was performed to determine why the number of PV trips was only reduced by one, when it was expected that two commute trips would be eliminated. A comparison of the VMT figures shows that telecommuting caused a 34.6 mile average reduction roughly equivalent to the telecommuters' approximate 33.9 mile average round trip commute distance. Thus, at first glance, it appeared as though the full round trip commute distance was eliminated plus 0.7 miles of non-commute VMT. However, non-commute related travel apparently increased by one (short) trip to account for the observed *net* reduction of just one trip. Because the potential for increasing non-commute travel has been an important hypothesized negative impact of telecommuting (see, e.g. Salomon, 1985), the analysis focused on determining more precisely how the reductions in trips and VMT were distributed between commute and non-commute purposes.

The issue was complicated by the fact that it was not possible to disaggregate the total average daily VMT into commute-related and non-commute-related with complete precision. For 15% (6) of the telecommuters, no direct home-to-work or work-to-home trips were recorded during the diary period. When, say, the trip to work was linked with a non-commute activity, it could not be determined how much of the home-other-work distance was attributable to the commute and how much to the non-commute activity. Thus, the average PV commute length for the entire sample of 40 telecommuters may be less than or greater than 33.9 miles by an unknown amount. Further, it should be noted that 33.9 miles is the average PV commute length counting the 34 applicable telecommuters only once each. The number of diary days and commute trips reported by each respondent varied somewhat, however, and to ascertain the proportion of total sample VMT that is due to commuting, a commute trip should be counted as often as it appears in the sample, not just once per respondent. With this background, then, the more detailed investigation of trip and VMT reductions revealed several interesting findings.

First, even though only weekdays (Monday–Friday) were analyzed, *Wave 1 days did not always involve a commute*. In fact, commute trips involving a PV (i.e. a PV was used for at least one leg of a trip sequence to or from work) were reported for only 75% of Wave 1 person-days. This is due to the natural inclusion of events such as all-day work-related meetings outside the main office, sick days, personal leave days, and commutes by non-PV modes in this sample. However, this has two implications. First, the average VMT per person-day of 44.8 miles for Wave 1 was smaller than it would have been if PV commute trips had been made on 100% of the person-days. Second, the average number of daily PV commute trips for Wave 1 was not two, but rather equal to 1.6. This figure was computed by counting the number of home-to-work sequences in the sample involving a PV (whether or not there were any intermediate trips), multiplying by two, and dividing by 114, the number of person-days in Wave 1.

This suggests that, for this sample, telecommuting might be expected to eliminate 1.6 PV trips rather than two. However, the second noteworthy observation drawn from closer inspection of the data is that *TC days did not always eliminate the commute*. On 6% of TC person days (3 days), at least one PV commute trip was reported. Of the 40 telecommuters in the sample, three were apparently telecommuting partial days and still making the trip to the regular office. This finding also has two implications, complementary to the first finding. The first implication is that the TC day average VMT was larger than it would have been if no PV commute trips had been made on TC days. The second implication is that the average number of PV commute trips on TC days was not zero as expected, but rather 0.1.

Taken together, these two findings mean that if non-commute trips did not change, we would expect to find a reduction of 1.5 PV trips on TC days. Since we instead find a reduction of 1.0 trips, we conclude that non-commute PV trips increased by 0.5 trips on average. Hence, the 27.4% reduction in trips reported in Table 4 may be viewed as the net of a 40.7% decrease in total PV trips due to eliminating the commute and a 13.3% increase in total PV trips due to non-commute trip generation.

Determining the impact of telecommuting on non-commute VMT is, as mentioned earlier, more problematic. The following procedure was used. For the majority of participants with a known commute length, each time a sequence of trips was made that started at home and ended at work, the known one-way commute length was counted as the commute portion of that trip sequence. For one participant whose commute length was not known, a one-way commute distance was slightly over-estimated by averaging the lengths of all trip sequences starting at home and ending at work (including all intermediate trips to non-work destinations). Five participants never made commute trip sequences involving a PV during the travel diary period and hence do not contribute anything to the total commute VMT of the sample.

Focusing on the home-to-work chain was based on the assumptions that more non-work activities chained to the commute trip (e.g. eating, shopping) occur in the afternoon than in the morning, that morning non-work destinations such as day care or school are

Table 5. Impacts of telecommuting on commute vs. non-commute VMT

	Telecommuters Wave 1	Telecommuters Wave 2 TC days	Difference
Total VMT	44.8	10.2	34.6
Commute VMT	29.5	0.2	29.3
Non-Commute VMT	15.3	10.0	5.3

likely to be closer to home on average than the more diverse afternoon destinations, and therefore that the morning commute is likely to provide a more accurate estimate of the one-way commute length than the afternoon commute. The total one-way PV commute distance for the entire group was then doubled (to approximate the round-trip commute distance), and divided by the number of person-days in the group to obtain a per-person-day average.

Table 5 presents the estimated values of average commute and non-commute VMT for the before and after (TC day) samples, respectively. Non-commute VMT was calculated as the difference between total and commute VMT. Analysis of the table shows that the 34.6 mile reduction in VMT on TC days comprises a decrease of 29.3 commute miles and a decrease of 5.3 non-commute miles. That is, although telecommuting *increased* the number of non-commute trips by 0.5, the non-commute VMT *decreased* by 5.3 miles. Thus, the telecommuters made shorter, but slightly more frequent PV non-commute trips on their TC days. The finding here is consistent with empirical results from the Puget Sound project, which noted a decrease of 1.1 PV trips on telecommuting days, comprising a decrease in commute trips of 1.4, with an increase in non-commute trips of 0.3 (Henderson *et al.*, 1996). In that study, non-commute VMT actually increased by 2.2 miles. But in both cases, the net impact on both trips (especially cold starts) and VMT is a considerable reduction.

4.4. Emissions findings

Table 6 summarizes the emissions findings of the study. Comparing the g/day emissions of telecommuters before telecommuting (Wave 1) and after telecommuting (Wave 2, TC Days) shows that vehicle emissions are greatly reduced as a result of telecommuting. A more reliable measure than the g/mile saved, the percent savings, shows emissions reductions of 48% for TOG, 64% for CO, 69% for NOx, and 78% for PM. Savings of this magnitude are expected given the dramatic decreases in VMT and number of trips shown in Table 4. Statistical testing is not performed on the emissions analysis component of this research since the emissions models do not provide output on an individual level, only aggregates for the entire sample.

The following discussion of results focuses on three key emissions-producing vehicle activities (VMT, cold starts, and average speeds) and how impacts due to telecommuting influenced vehicle emissions. VMT, a surrogate for running emissions, has been shown to be the primary contributor to PM and NOx. The 77% reduction in VMT on TC days is a

Table 6. Emissions impacts of telecommuting (average g/person-day)

	Telecommuters			Controls	
	W1 40 people 114 days	W2 TC days 40 people 52 days	W2 NTC days 34 people 56 days	W1 58 people 161 days	W2 57 people 149 days
TOG*	56.93	29.37	48.78	49.32	52.31
CO*	291.44	103.49	215.89	216.52	206.48
NOx*	41.10	12.59	30.27	31.36	33.19
PM*	9.61	2.10	7.95	6.94	6.65

* Measured in g/person-day.
Statistical tests could not be performed on these measures, because the model does not produce emissions by individual and therefore standard deviations could not be computed.
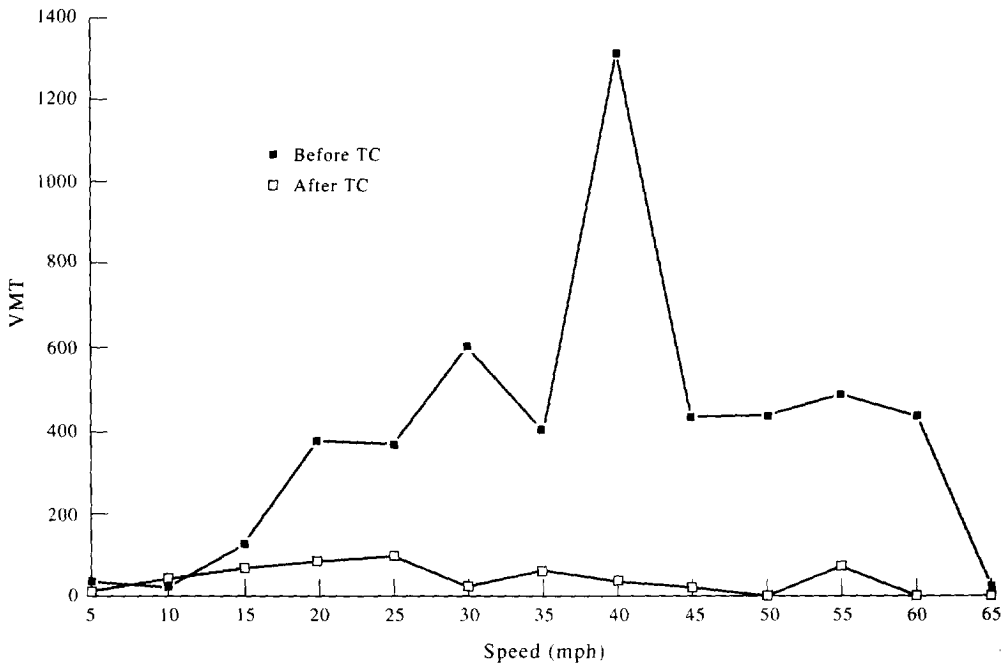
Fig. 2. VMT vs speed.

primary reason for the large decrease in the emissions of all pollutants, but especially PM and NOx, with 78 and 69% reductions, respectively.

Engine starts, particularly cold starts, are another major cause of pollutant emissions. Cold starts are the primary contributors to TOG and CO emissions for short-to-medium length trips (20 miles). Telecommuters in this sample had 39% fewer cold starts on TC days (comparing Table 4; columns 1 and 2), a reduction from 2.5 to 1.5 per day. This resulted in 50 and 52% decreases in those portions of TOG and CO emissions that related specifically to cold starts.

4.5. Speed distribution analysis

The emissions savings calculated for this pilot project were caused by decreases in many key emissions-producing vehicle activities including VMT and (cold start) trips. Average vehicle speed, however, decreased on telecommuting days to speeds associated with higher emissions rates. Previous studies (Sampath *et al.*, 1991) have noted a similar result due to telecommuting reducing the proportion of freeway VMT, resulting in lower average trip speeds. The average speed of telecommuters in this sample decreased from 38 mph before telecommuting to 27 mph on TC days. Further analysis was performed to determine more specifically the basis for the observed shift in average speed.

Figure 2 shows the distribution of the total VMT across the sample at various speeds for the telecommuters before and after telecommuting. VMT is plotted on the ordinate with average trip speed on the abscissa. The figure illustrates that VMT is reduced in essentially every speed category. Thus, although the average trip speed is reduced as a result of telecommuting, the reduction is due to a larger decrease in high speed VMT, not to a re-distribution of VMT to lower speeds. This means that rather than individual trips being made at lower speeds on telecommuting days, the higher-speed travel on non-telecommuting days (the commute) is just eliminated, effectively reducing the *average* trip speed. Thus the reduction in average trip speed should not be considered a cost of telecommuting, only a logical consequence of the nature of the VMT savings.

Further, it should be noted again that an analysis based on average speeds, although currently the best the models and data permit, is incomplete. It is also important to understand better the emissions effects due to changes in accelerations and decelerations.
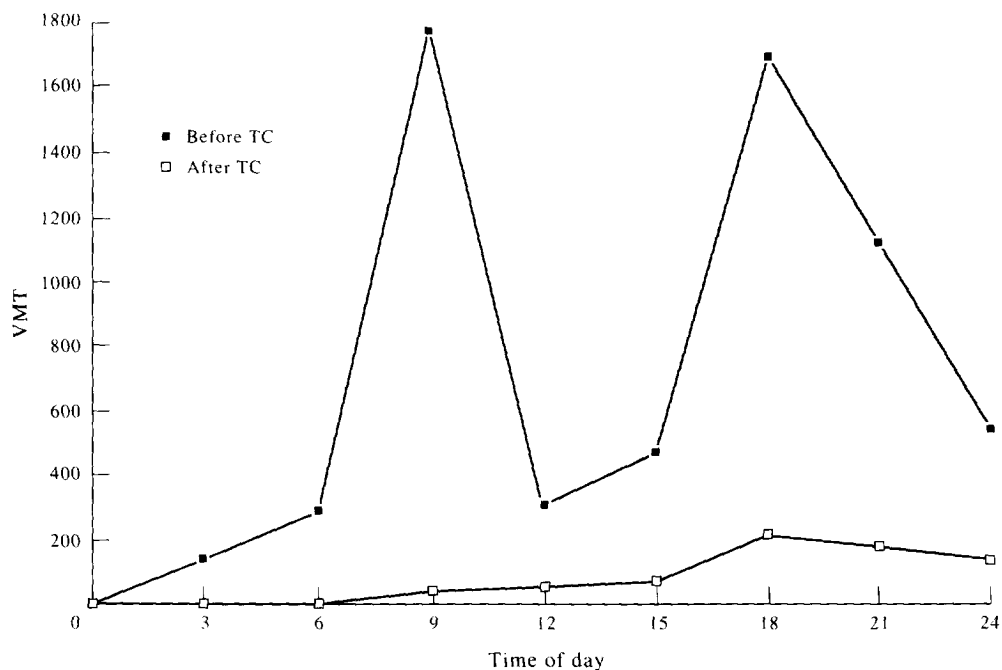
Fig. 3. VMT vs time of day.

These effects cannot currently be modeled at the individual level, nor, even if they could be, do standard travel diaries collect the information necessary to measure accelerations and decelerations for a given trip.

4.6. VMT/time of day distribution analysis

Another interesting measure of travel behavior is the distribution of VMT throughout the day and how that distribution changes with telecommuting. Figure 3 shows a plot of the total VMT for the sample against time of day with VMT on the ordinate and time of day on the abscissa. Analysis of the figure reveals that telecommuting caused a reduction in VMT during every time period of the day. The largest reductions took place between midnight and 12 noon. The morning peak corresponding to the morning commute hour is eliminated. A relatively high proportion of travel on telecommuting days still occurs in the p.m. peak, but the absolute level of travel during that time period is greatly reduced. This change in travel behavior patterns is expected to have at least two beneficial impacts.

First, the reduction in VMT will contribute to decreases in both running emissions and traffic congestion. While this study focuses on the direct emissions impacts of telecommuting, it is obvious that, all other parameters being equal, congestion will be reduced if travel is reduced or eliminated during peak period times. This in turn could have an indirect emissions benefit by smoothing traffic flow. It is sometimes argued that the reduction in travel demand due to telecommuting will be negated when demand that has been latent due to congestion is released after that congestion has been mitigated. Only one study to date (DOE, 1994) has attempted to quantify this feedback effect. The study constructed a number of scenarios to assess the effects of telecommuting under a range of assumptions about telecommuting levels, indirect effects, and emissions levels. The analysis indicated that although the realization of latent demand tends to reduce the direct benefits of telecommuting, there are still non-trivial net benefits even under the worst case assumptions.

The second impact has to do with the distribution of trips by time of day. Figure 4 shows the proportional distribution of VMT vs time of day. The figure shows that telecommuting caused disproportionate reductions in VMT (hence travel) across the day. Specifically, VMT was decreased more in the morning (midnight to noon) than in the
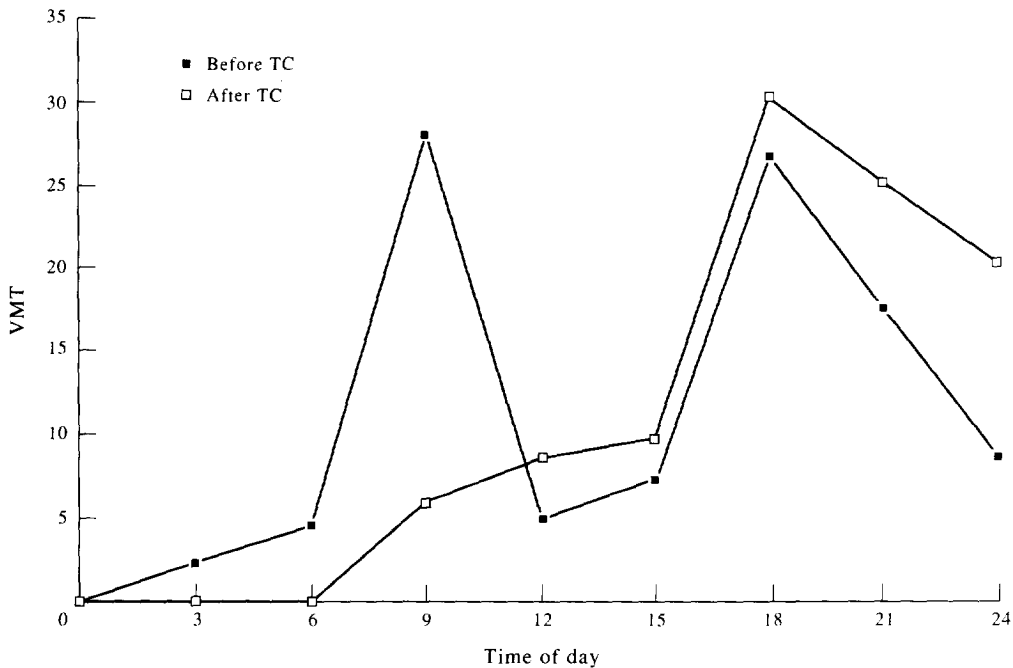
Fig. 4. Proportion of VMT vs time of day.

other time periods. The benefit from this disproportionate reduction in travel is greater than if the reduction had been equal in each time period, since it is more desirable to eliminate cold engine starts in the morning than in the afternoon. In the Puget Sound study, 10–12% of the total emissions savings could be attributed to cold starts taking place at warmer ambient temperatures (Henderson et al., 1996). Therefore, the larger reductions in morning travel contribute to reduced cold start emissions, an important factor in the overall emissions savings. However, the largest contribution to the emissions reduction is the dramatic decrease in travel in every time period.

4.7. D/C ratio

It is desirable to compare the findings reported here to the findings from other studies to determine the relative efficiency of telecommuting programs and other TDMs. To decrease vehicle emissions, TDMs typically focus on reducing either distance traveled (VMT) or the number of (cold start) trips, or both. Research on emissions-producing vehicle activities has shown that VMT is analogous to running emissions (impacting PM and NOx most heavily), while the number of cold starts is analogous to cold start emissions (impacting CO and TOG most heavily). Using these activities as surrogates for emissions permits a rough assessment of the emissions impacts of various TDMs without requiring use of data-intensive emissions models. The Distance/Cold start Ratio, or D/C Ratio (Henderson et al., 1996) allows this comparison to be made. The D/C Ratio is defined as:

$$D/C \ Ratio = \frac{\% \ reduction \ in \ VMT}{\% \ reduction \ in \ the \ number \ of \ cold \ starts}$$

For this study, the D/C Ratio has a value of 77/39 = 1.97. The quotient shows that the reduction in VMT is equal to 1.97 times the reduction in the number of cold starts. While these numbers show a significant (39%) reduction in the number of cold starts (CO and TOG), the ratio indicates that telecommuting was even more effective at reducing VMT (NOx and PM). It is important to note that a higher value of the quotient is not necessarily better, it only indicates the degree to which a TDM more heavily impacts

either VMT or cold starts. For air basins targeting specific pollutants for which they are in violation of federal air quality standards, the D/C Ratio may be a useful tool to identify those TDMs most effective at helping achieve compliance.

The D/C Ratio is also useful for comparing different studies of the same TDM. For example, the D/C Ratio from this study of telecommuting can be compared to the D/C Ratio of the Puget Sound Telecommuting Demonstration Project analysis (Henderson *et al.*, 1996) to determine similarities and differences between the two projects. For the Puget Sound Project the D/C Ratio had a value of 63/44 = 1.43. Comparing the two ratios shows that in both cases telecommuting was more effective at reducing VMT (NOx and PM) than cold starts (TOG and CO). Analyzing the numerator and denominator of the ratio independently identifies two important findings. The Puget Sound telecommuters reduced cold starts more than the State of California participants (44–39%). The opposite occurred with total travel, however, where VMT reductions for the two groups were 63 and 77%, respectively. These findings show that while the magnitude of travel and emissions reductions due to telecommuting may vary from one study to another, there is a growing body of evidence that telecommuting causes significant reductions in both VMT and the number of cold starts, with VMT being the most heavily influenced.

5. CONCLUSIONS/RECOMMENDATIONS FOR FUTURE RESEARCH

The purpose of this research was to investigate the impacts of telecommuting on travel behavior and personal vehicle emissions levels. A methodology was developed that utilizes data obtained from travel diaries, with information collected on a trip-by-trip basis. This data was entered into the CARB's emissions models, EMFAC7F and BURDEN7F, to estimate the emissions levels of each participant group before and after telecommuting, and to determine the relative changes in emissions levels among groups. A comparison of participants' telecommuting day travel behavior with their before-telecommuting behavior shows a 27% reduction in the number of personal vehicle trips, a 77% decrease in vehicle-miles traveled (VMT), and 39% (and 4%) decreases in the number of cold (and hot) engine starts. These decreases in travel translate into emissions reductions of 48% for total organic gases (TOG), 64% for carbon monoxide (CO), 69% for nitrogen oxide (NOx), and 78% for particulate matter (PM).

Disaggregating the daily travel (for the telecommuting sample before and after on TC days) into commute and non-commute trips and VMT showed that the 34.6 mile reduction in VMT on TC days comprised a decrease of 29.3 commute miles and a decrease of 5.3 non-commute miles. Analysis revealed that although the net reduction in the number of trips was one, 1.5 commute trips had actually been eliminated, meaning that telecommuting caused an *increase* in the number of non-commute trips by 0.5. Thus, the telecommuters made shorter, but more frequent non-commute trips on their TC days. The finding here is consistent with empirical results from the Puget Sound project, which noted a decrease of 1.1 trips on telecommuting days, comprising a decrease in commute trips of 1.4, with an increase in non-commute trips of 0.3 (Henderson *et al.*, 1996). In both cases, however, non-commute VMT decreased, and of course the net impact of telecommuting on both trips (specifically cold starts) and VMT leads to considerable reductions in travel and emissions.

Non-commute trip generation has been identified as a potential negative impact of telecommuting. The empirical results to date on this issue have been encouraging, with relatively small fluctuations in non-commute travel being observed. Although the magnitudes and directions of these fluctuations may vary from study to study, they are not expected to negate the transportation and emissions benefits of telecommuting. Nevertheless, this issue should continue to be studied, since non-commute travel impacts may change considerably as shorter-distance commuters adopt telecommuting in greater numbers (Mokhtarian *et al.*, 1995). Further, it would be valuable to include household members in future analyses. To date, the travel impacts of telecommuting on household members have not been well studied due to the difficulty in obtaining sufficient data.

The methodology developed here involves using travel diary data from a sample of individuals to evaluate the emissions impacts of telecommuting for that sample. However, the methodology may be used to evaluate the emissions impacts of *any* transportation strategy for which travel diary data have been collected. An evaluation of the emissions impacts of a particular transportation measure is an important part of the policy-making process. Because travel behavior and emissions are closely but not monotonically linked, an analysis of both allows multi-dimensional considerations to be made. It is important to note, however, that in this paper, the percent changes (in travel and emissions) due to telecommuting represent average per capita, per occasion reductions. Thus, a comparison of the aggregate effectiveness of two measures must take into account the number of people likely to be affected by each measure and the percentage of days that the measure is implemented, not just the per capita, per occasion impacts. Although this level of analysis is beyond the scope of the present paper, aggregate trends of the adoption of telecommuting are discussed in Handy and Mokhtarian (1995), Handy and Mokhtarian (1996).

A number of interesting research questions remain regarding the transportation-related impacts of telecommuting. One of particular relevance to the subject of this paper is the transportation and emissions impacts of telecommuting from a center compared to tele-commuting from home. Center-based telecommuting, by definition, requires a commute of some kind (albeit shorter than the trip to the conventional workplace), and therefore may involve a cold start. Policymakers are reluctant to fully support telecommuting cen-ters as a TDM strategy until more is known empirically about their effectiveness in redu-cing emissions. Multiple projects are currently underway by the latter two authors to evaluate center-based telecommuting by comparing VMT, number of trips, commute mode choices and trip linking characteristics of telecenter users with those of home-based telecommuters and non-telecommuters of the same organization. These and other studies will continue to provide useful new insights into the travel and air quality-related impacts of telecommuting.

Future efforts should be made to extend these types of analyses to include an investi-gation of the non-work day impacts of telecommuting, as well as comparisons of tele-commuting household members with non-telecommuting household members. These analyses would help to answer some important questions such as whether telecommuting causes shifts in an entire household's travel behavior and whether telecommuting shifts travel between weekend and work week days. Dats sets currently available do not contain sufficiently reliable weekend and household data to perform such an analysis. It has pro-ven to be a challenge to collect data of this type, especially from non-telecommuting households where there is little or no incentive to fill out travel diaries.

Future research on the emissions impacts of telecommuting will benefit from improve-ments to the EMFAC/BURDEN models. It is expected that the upcoming (7G) versions of the models will increase predicted emissions levels to be more consistent with field-measured pollutant concentrations (Washington, 1994). These advances will improve the estimates of emissions levels allowing for more accurate comparisons of the emissions benefits of telecommuting and other TDMs.

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