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Beyond Tele-substitution:
A Broader Empirical Look at
Communication Impacts

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CALIFORNIA PARTNERS FOR ADVANCED TRANSIT AND HIGHWAYS

ABSTRACT

Information on the number and types of communication activities (including travel) engaged in over a period of four consecutive days, at two points in time about six months apart, was collected from 91 respondents. A system of structural equations was developed and estimated, expressing the quantity of each type of communication at time *2* as a function of quantities of communication of each type at time *1*, the elapsed time between measurements, and exogenous sociodemographic variables. All "own" lagged effects (that is, the effect of one communication type in wave *1* on the *same* type of communication in wave *2*) were found to be positive and (except for information object delivery) highly significant. The "elapsed time" variable was always positive and (except for personal meetings and, in one model, information object delivery) significant; these effects indicate net generation of communication activities over time. Significant "cross" lagged effects (that is, the effect of one communication type in wave *1* on a *different* type in wave *2*) were mostly positive, indicating that the predominant effect across modes is complementarity rather than substitution. Several exogenous variables were also significant in logical ways.

EXECUTIVE SUMMARY

A number of empirical studies of the impact of telecommuting on travel have found net reductions in trips and distance traveled – that is, substitution of telecommunications for travel. But there is considerable conceptual, anecdotal, and empirical evidence suggesting a stimulation or generation effect as well. It may be that focusing on a specific application such as telecommuting will underestimate stimulation effects, which tend to be longer-term and more indirect (occurring outside the boundaries of the process being studied), in favor of the shorter-term and more direct substitution effects. What is needed is a comprehensive look at all forms of communication and their impacts on each other, over time. An initial step toward an analysis of that nature is presented here, using structural equations modeling of communication diary data.

The conceptual framework which underlies the present empirical analysis views all communication as requiring some form of transportation in order to occur. The three major "modes" of communication are meeting *in person* (requiring personal travel); transferring a *physical object* containing information (requiring "freight transportation" of some sort); and sending *electronic* signals (requiring the transportation of bits of data). Thus, passenger travel, goods movement of "information objects", and telecommunications may be regarded as alternate modes of communication, each with various submodes. At least four types of cross-mode impacts are possible: *substitution, generation, modification, and neutrality*.

The approach taken in this study is to collect data on engagement in many types of communication activities, rather than to focus on a single "tele-application" such as telecommuting and its direct transportation impacts. These data are collected by means of a communication diary, in which respondents record instances of communication in a number of categories, over several consecutive days, at two points in time approximately six months apart.

The Davis Community Network (DCN) offered the empirical context for this study. The City of Davis, California (population 50,000) is located 15 miles from the state capital of Sacramento; many Davis residents work for the state government. The major employer in Davis is the

University of California. DCN was launched slowly, beginning in January 1994, and is still in operation. At the time collection of the evaluation data was completed in June 1995, the main features of the system were electronic mail, newsgroup-reading, and web-browsing capabilities. In view of that, the evaluation constituted primarily an assessment of the impact of Internet access on communication and transportation.

The final estimation sample for this analysis contained 91 respondents who completed and returned both waves of the communication diary as well as the background survey obtaining information on demographic characteristics. The sample was very well educated, relatively affluent, and highly computer literate. Two-thirds of the sample was male, more than a third had children under 16 in the household, and the median age was approximately 42.

Six communications (sub-)modes were analyzed in this study: phone, fax, e-mail, information object transfer, personal meetings, and trips. Looking first at aggregate changes in communication mode use on weekdays, the percent of weekdays on which phone, fax, and personal meeting communications took place declined somewhat between waves, whereas the opposite was true for e-mail. This suggests that, on net, traditional forms of communication are to some extent being replaced by e-mail. Similar but not identical results are shown by daily communication rates, which decrease significantly for phone and personal meeting, and increase for fax, but change very little for the other modes, including e-mail. The weekend patterns show a more mixed picture.

A system of disaggregate structural equations was developed and estimated, expressing the quantity of each type of communication at time *2* as a function of quantities of communication of each type at time *1*, the elapsed time between measurements, and exogenous sociodemographic variables. All "own" lagged effects (that is, the effect of one communication type in wave *1* on the *same* type of communication in wave *2*) were found to be positive and (except for information object delivery) highly significant. The "elapsed time" variable was always positive and (except for personal meetings and, in one model, information object delivery) significant; these

effects indicate net generation of communication activities over time. It is interesting but not surprising that the newest (and in many ways most convenient) mode of communication – e-mail – is the most rapidly growing one, and that the oldest (and potentially most time-consuming) one – personal meetings – is the slowest growing. However, it is important to note that trips have the second-highest rate of growth. Clearly, trips are not disappearing in favor of telecommunications.

Significant "cross" lagged effects (that is, the effect of one communication type in wave *1* on a *different* type in wave *2*) were mostly positive, indicating that the predominant effect across modes is complementarity rather than substitution. Specifically (in the endogenous-only effects model), phone has a positive impact on information objects; information objects have a positive impact on phone and personal meetings; and personal meetings and trips each have a positive impact on the other. Several exogenous variables were also significant in logical ways.

As initially applied here, the longitudinal disaggregate structural equations modeling approach had several limitations, including a small sample size, the primitive nature of the activity indicator (number of events in each category), and only an indirect inference of causality. Nevertheless, we believe this approach holds considerable promise as a way to analyze the multi-directional relationships among different means of communication. Improved insight into telecommunications - travel relationships is sure to result.

1. INTRODUCTION AND CONCEPTUAL FRAMEWORK

A number of empirical studies of the impact of telecommuting on travel have found net reductions in trips and distance traveled – that is, substitution of telecommunications for travel (see Mokhtarian, *et al.*, 1995 and Mokhtarian, 1998 for reviews of these studies). But there is considerable conceptual, anecdotal, and empirical evidence suggesting a stimulation or generation effect as well (see Salomon, 1986; Mokhtarian, 1990; Mokhtarian and Salomon, 1997; Niles, 1994). It may be that focusing on a specific application such as telecommuting (or teleconferencing, or teleshopping, or ...) will underestimate stimulation effects, which tend to be longer-term and more indirect (occurring outside the boundaries of the process being studied), in favor of the shorter-term and more direct substitution effects. What is needed is a comprehensive look at all forms of communication and their impacts on each other, over time. An initial step toward an analysis of that nature is presented here.

Mokhtarian (1990) introduces the conceptual framework which underlies the present empirical analysis. This framework views all communication as requiring some form of transportation in order to occur. The three major "modes" of communication are meeting *in person* (requiring personal travel); transferring a *physical object* containing information, such as a book, letter, or diskette (requiring "freight transportation" of some sort); and sending *electronic* signals (whether wire-based or over the air), such as telephone, fax, e-mail, and videoconferencing, as well as television and radio (requiring the transportation of bits of data). Thus, passenger travel, goods movement of "information objects", and telecommunications may be regarded as alternate modes of communication, each with various submodes.

At least four types of cross-mode impacts are possible, two of which have already been mentioned. *Substitution* occurs when the use of one mode (e.g. electronic communications supporting telecommuting) reduces the use of another (personal travel for commuting). *Generation* (stimulation, complementarity) occurs when the use of one mode increases the use of another (the more one travels, the greater the opportunity to use a mobile phone; the greater the availability of information about activities and people of interest, the greater the travel to

participate in those activities or meet those people). *Modification* occurs when the use of one mode alters something about the use of another mode, where the use still takes place (so it is not substituted) and would have taken place anyway (and so is not generated), but is now modified (a phone call changes the time or destination of a trip; real-time congestion information received over the radio or computer changes the route of a trip). Depending on how the use of a mode is measured, instances of modification may fall under one of the first two categories. For example, if the measure of personal transportation is vehicle-kilometers traveled (VKT), then a route or mode change will result in fewer (substitution) or more (generation) VKT. *Neutrality* occurs when the use of one mode has no impact on other modes (an e-mail message may have no impact on other modes of communication, although it may have the "own-mode" impact of generating more e-mail messages).

Mokhtarian (1990) and others have suggested that the total amount of communication is expanding, through both own-mode and cross-mode generation effects. Thus, as schematically illustrated in Figure 1, substitution across modes may result in changing mode shares, but the absolute amounts of communication in all modes could continue to increase. It can be seen, then, that a study of, say, the impacts of telecommuting on travel presents an incomplete picture, focusing as it does on only one direction of impact and between only two modes, instead of examining the complete set of interconnecting relationships among modes.

The remainder of this paper presents and applies a methodology for analyzing this set of interconnecting relationships: structural equations modeling of communication diary data. The next section describes the methodology in general terms. Section 3 presents the empirical context of the initial application of the methodology. Section 4 examines the key results. The final section summarizes the results and discusses the limitations of the methodology.

2. METHODOLOGY

2.1 The Communication Diary and Associated Measurement Challenges

The approach taken in this study is to collect data on engagement in many types of

communication activities, rather than to focus on a single "tele-application" such as telecommuting and its direct transportation impacts. These data are collected by means of a communication diary, in which respondents record instances of communication in a number of categories, over several consecutive days, at two (or more) points in time several months apart.

FIGURE 1
RELATIONSHIPS AMONG COMMUNICATION MODES

electronic
transmission

information
freight

personal
travel
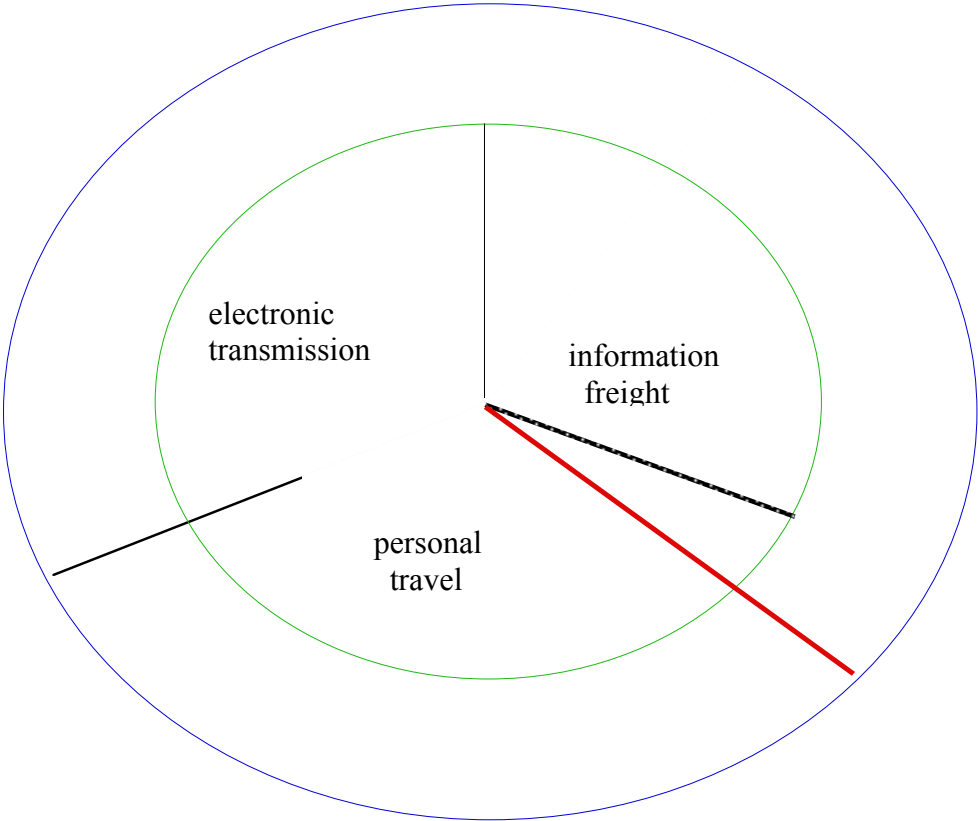
Source: Mokhtarian (1990)

Transportation analysts are familiar with the trip diary as a way of measuring travel behavior (Axhausen, 1995). More recently, activity or time use diaries have begun to be used for similar purposes, with advantages and disadvantages relative to travel diaries (Axhausen, 1997; Pas, 1997). Focusing on measuring communication, however (as a subset of all activities) presents a number of practical difficulties. Are all forms of communication important? Reading a billboard or watching television are one-to-many, passive forms of communication which nevertheless can have impacts on transportation (shopping for an advertised product or attending an advertised event) or on other forms of communication (calling a friend to discuss the outcome of the televised football match). Yet providing data on the total input and output of communication would be quite cumbersome for the respondent.

Tied to the question of which types of communication should be included, how much information should be requested for each communication instance? Travel diaries obtain a considerable amount of information on each trip (origin, destination, start time, end time, mode, purpose, number of people traveling, distance, cost) – and that is acknowledged to be a heavy burden for the respondent. Yet most people engage in many more communication activities than in trips, and so requesting the same level of information for communication activities would likely be unreasonable unless only a subset of activities was selected (in which case the measurement of total communication, and hence the assessment of impacts, would of course be incomplete).

And what should be the units of measuring communication? The number of communication activities is the simplest unit – but limited, since there may be, for example, a tradeoff between number of communications and time spent on each communication. Hence, a finding that the number of communication activities is increasing does not necessarily mean that the total time spent on communication is increasing. (Is there a communication time budget, analogous to the much-discussed travel time budget?) The amount of time spent in communication, then, is another important unit – but also limited, since it does not measure the actual quantity of information conveyed. Fifteen minutes spent reading the newspaper, for example, conveys much

more information than 15 minutes spent composing an e-mail message. But how will quantity of information be measured, especially over very disparate forms of communication? And how can quality and value of information be accounted for? Reading the newspaper may convey a greater quantity of information, but the e-mail message may contain information of higher quality and greater value. This is a critical issue, since the decision whether or not to substitute tele-communications for travel will very much depend on the relative quality of the information obtained in each case.

Further, there is the issue of the temporal dimension, which is important to the measurement of impacts of each form of communication on the others. Some impacts may occur almost immedi-ately while others take months to be realized. In view of the current impracticality of collecting data on all communication activities continuously over a long period of time (although it may be technically possible to do so for many or most *tele*communication activities), it seems unrealistic to expect to measure specific impacts of one communication activity on others (however, one imperfect, self-reported approach for doing that for a single type of communication activity is described in Balepur, 1998). The best that can be hoped for is to capture general trends associating levels of communication in one mode at one point in time with levels of communication in that and other modes at a later point in time.

Several researchers have used communication diaries in some form. Claisse and Rowe (1993) had 663 respondents in the Lyon, France metropolitan area keep a one-week diary, but only of residential telephone calls. Moberg (1993) used a diary to study differences in communication patterns between workers at satellite work centers and those at corporate headquarters for three Swedish companies. Spittje (1994) collected seven-day activity diary data, including information on trips and use of phone, fax, and e-mail, from 209 respondents (both telecommuters and non-telecommuters) in the Netherlands. Perhaps the most comprehensive measurement of communication using the diary approach is described by Zumkeller (1996). He and his colleagues adapted a typical trip diary to obtain information on "contacts" as well as trips in the order in which they occurred. Similar information was obtained for both trips and

contacts: time, mode, purpose, and distance. Empirical results, for a one-day period, have been reported for a pilot sample of 166 people associated with the University of Karlsruhe, Germany; larger data collections and analyses are underway.

The diary used in the present study is simpler in some ways than those described above. It asks only for a tally of the number of communication activities in each of various categories (fixed-location phone calls initiated and received; similarly for mobile phone calls, faxes, e-mail, in-house memos or documents, express mail/overnight packages, and all other documents by mail except "junk" mail; number of meetings and number of people present in the three categories of class or conference, other work-related, and other; and number of trips and number of miles by each of drive-alone, shared-ride, walk/bike, public transit, and other modes). Thus, while all three main modes of communication are represented, submodes were selectively chosen to focus primarily on interactive communications. Respondents were asked to complete the diary for four consecutive days (starting either on a Sunday or a Wednesday, so that data would be obtained for one weekend day and three weekdays), and, unlike any of the examples mentioned above, completed the diary at two points in time approximately six months apart.

2.2   Structural Equations Modeling

Structural equations modeling has been used extensively in economics and the social sciences to examine the interrelated effects of multiple endogenous variables on each other (Dwyer, 1983; Hoyle, 1995; Mueller, 1996). Recently, it has been applied in travel behavior modeling and time use, to analyze relationships between travel time and activity engagement (Golob, 1990; Lu and Pas, 1997; Gould and Golob, 1997). In particular, Gould, *et al.* (1998) use the technique on activity diary data, to shed some light (indirectly) on potential telecommunication/travel tradeoffs.

Here, structural equations modeling is used to identify the impact over time of each communication mode on all other modes (including itself). Let E_{ti}, O_{ti}, and PM_{ti} represent the daily average numbers of electronic communications, information objects transferred, and personal meetings,

respectively, reported by individual i at time t ($t = 1, 2$). In the empirical analysis below, some submodes are distinguished; here we treat only major modes for economy of presentation. Then the structural equations model may be written generically as:

$E_{2i} = f(E_{1i}, O_{1i}, PM_{1i},$ elapsed time$_i$, seasonal dummies$_i$, socioeconomic variables$_i$, error term$_{iE}$)

$O_{2i} = f(E_{1i}, O_{1i}, PM_{1i},$ elapsed time$_i$, seasonal dummies$_i$, socioeconomic variables$_i$, error term$_{iO}$)

$PM_{2i} = f(E_{1i}, O_{1i}, PM_{1i},$ elapsed time$_i$, seasonal dummies$_i$, socioeconomic variables$_i$, error term$_{iPM}$).

Cross-mode coefficients (e.g. the coefficients of O_{1i} and PM_{1i} in the equation for E_{2i}) represent the lagged effects of one mode (information objects and personal meetings, respectively) on another (electronic communications). A positive coefficient implies a generation effect (high levels of one mode at time *1* are associated with high levels of the other mode at time *2*, or conversely), and a negative coefficient implies a substitution effect (high levels of one mode at time *1* are associated with low levels of the other mode at time *2*, or conversely). Own-mode coefficients (e.g. the coefficient of E_{1i} in the equation for E_{2i}, sometimes referred to as "inertia" or "stability" effects) capture the effect of communication by a certain mode on later communication by the same mode, and would generally be expected to be positive (high levels at time *1* associated with high levels at time *2* or conversely) unless some sort of cyclical or dampening effect is at work.

The "elapsed time" variable is the time between the two waves of data, which varies by individual (although relatively little, in this sample). The coefficient of this variable represents changes over time in numbers of communication activities by the mode in question, after other effects are accounted for. It may be interpreted as a background trend, or the average effect of unobserved variables; thus it plays a role similar to that of a constant term in a static equation. In fact, because elapsed time did not vary greatly across the sample studied here (mean = 27.1 weeks, s.d. = 7.9 weeks), it essentially replaces the constant in each equation; including both terms resulted in collinearity effects. A positive coefficient means that communication by that

mode is generally increasing over time, all else equal.

Because the two waves of data were collected six months apart (a constraint of project imple-
mentation timing and funding availability rather than by intention), seasonal differences in levels
of communication could partially account for the observed results. The seasonal dummies help
control for that factor by capturing the average effects of those seasonal differences. In this
sample, all the second-wave data were collected in spring (April - June 1995). The first-wave
data spanned summer (with all but one observation occurring in September, 34.0%), fall
(October - December, 46.2%), and winter (January - March, 19.8%) quarters. Taking summer as
the base, fall and winter dummy variables were created to represent first-wave data collection in
those respective quarters. A positive coefficient for quarter q in equation j means that (all else
equal) first-wave data collected in quarter q show a stronger and more positive effect on second-
wave communications by mode j than do first-wave data collected in the base quarter.

Finally, socioeconomic variables capture the effect of individual characteristics such as occupa-
tion, income, age, and household size on levels of communication.

In the generic model system described above, all right-hand side (RHS) endogenous variables are
lagged. If it could be assumed that lagged endogenous variables for mode j are uncorrelated with
the error terms of the equations for mode j^*, $j^* \neq j$, then it would be appropriate to apply ordinary
least squares (OLS) regression equation-by-equation to estimate the coefficients of the system.
Although this is sometimes adopted as a reasonable assumption in this type of equation system,
we take a more cautious approach (which is later justified by the outcome, shown in Table 6),
and jointly estimate the coefficients of all equations simultaneously while allowing for the error
terms to be correlated across equations. The AMOS module of the SPSS software package
(Arbuckle, 1997), using maximum likelihood estimation, is employed to obtain the results
presented here. Very similar results were obtained from the Seemingly Unrelated Regression
Equations (SURE) module of the LIMDEP software package (Greene, 1995), which uses
generalized least squares (GLS) methodology.

3. EMPIRICAL CONTEXT

The Davis Community Network (DCN) offered the empirical context for operationalizing the methodology described in the previous section. The City of Davis, California (population 45,000) is located 15 miles from the state capital of Sacramento; many Davis residents work for the state government. The major employer in Davis is the University of California.

DCN was launched slowly, beginning in January 1994, and is still in operation. At the time collection of the evaluation data was completed in June 1995, the main features of the system were electronic mail, newsgroup-reading, and web-browsing capabilities. In view of that, the evaluation constituted primarily an assessment of the impact of Internet access on communication and transportation. That impact, especially on transportation, may not be expected to be sizable – particularly not as sizable as might be expected if more information about community activities had been posted and if more transaction opportunities had been available at the time of data collection. Nevertheless, the communication diary data offer a useful snapshot of levels of communication at two points in time, and support a meaningful model of the relationships among various forms of communication across time.

Multiple data collection instruments were developed for the evaluation. In the present context, two instruments are most relevant: the communication diary described in Section 2.1, and a background survey obtaining information on demographic characteristics. Another instrument, the activity diary, which collected data on the antecedents and likely consequences (for communication and travel) of a sample of DCN uses, has been analyzed by Balepur (1998).

The initial sample for this analysis contained 108 respondents who completed and returned both waves of the communication diary as well as the background survey. After screening the sample for missing data and outlier values on important variables, the final estimation sample size was 91. The characteristics of these 91 respondents are summarized in Table 1. Not surprisingly in view of the nature of Davis as a college town, the sample was very well educated, relatively

affluent, and highly computer literate. Two-thirds of the sample was male, more than a third had children under 16 in the household, and the median age was approximately 42.

It is useful to examine aggregate changes in communication mode use before turning to the disaggregate models. Table 2 summarizes sample activity indicators by mode, wave, and day type (distinguishing weekdays, Monday - Friday, from weekends). Here and subsequently, the electronic communication mode is subdivided into phone, fax, and e-mail submodes based on preliminary analysis suggesting that uses of these submodes are changing differently over time (confirmed by the results in Table 2). Further, data on both personal meetings and trips were collected, and are distinguished in Table 2 and in the structural equations models to follow. Both "submodes" are important. Trips are important, to be able to analyze the effect of communications on total travel, and personal meetings are essential as the key measure of the face-to-face mode of communication, but trips and personal meetings are not completely interchangeable measures. Not all trips (for example, grocery shopping trips) are undertaken for the primary purpose of communication (whether face-to-face or information object transfer), and conversely, not all personal meetings involve a trip, at least for the respondent (depending on how a "trip" is defined, multiple meetings occurring at the same location, such as work, may

TABLE 1
SAMPLE CHARACTERISTICS (N = 91)

Occupation		Gender	
Manager/administration	13 (14.3%)	Female	31 (34.1%)
Professional/technical	61 (67.0%)	Male	60 (65.9%)
Services/repair	2 (2.2%)	**No. of vehicles**	
Administrative support	7 (7.7%)	Per household	2.0 (s.d. 1.2)
Sales/marketing	2 (2.2%)	Per licensed driver	1.0 (s.d. 0.6)
Other	6 (6.6%)	**Average one-way commute**	
		Length (miles)	12.7 (s.d. 15.3)
Employment status		Time (minutes)	22.2 (s.d. 20.0)
Self-employed	17 (18.7%)	**Computer experience**	
Full-time employee	63 (69.2%)	Less than 1 year	3 (3.3%)
Part-time employee	11 (12.1%)	1 - 3 years	10 (11.0%)
		4 - 8 years	30 (33.0%)
		More than 8 years	47 (51.6%)
		Missing	1 (1.1%)
Average years with:		**Education**	
Employer	7.5 (s.d. 7.6)	Some college or tech school	6 (6.6%)
Occupation	10.6 (s.d. 8.0)	Four-year degree	21 (23.1%)
Household size		Some graduate school	15 (16.5%)
Average	2.7 (s.d. 1.3)	Completed graduate degree(s)	45 (49.5%)
No. with children under 16	35 (38.5%)	Missing	4 (4.4%)
No. with children under 6	14 (15.4%)		

----- continued -----

TABLE 1 (continued)			
Age		**Annual HH pretax income**	
20-24	3 (3.3%)	Less than $15,000	3 (3.3%)
25-34	20 (22.0%)	$15,000 - 24,999	8 (8.8%)
35-44	26 (28.6%)	$25,000 - 34,999	5 (5.5%)
45-54	32 (35.2%)	$35,000 - 54,999	29 (31.9%)
55-64	9 (9.9%)	$55,000 - 74,999	16 (17.6%)
65 or older	1 (1.1%)	More than $75,000	22 (24.2%)
		Missing	8 (8.8%)

not involve a trip[1]). There is a slight asymmetry in the data, as activity indicators for the electronic and information object modes and submodes combined "sent/initiated" and "received" communications (although they were measured separately in the diary), whereas "trips" only counted trips made by the respondent, not trips made by others to see the respondent (which were not measured by the diary). This is not expected to have a material effect on the substantive relationships found here.

Looking first at weekday patterns in Table 2, the "percent of inactive person-days" indicator implies that the percent of weekdays on which phone, fax, and personal meeting communications took place declined somewhat between waves, whereas the opposite was true for e-mail. This suggests that, on net, traditional forms of communication are to some extent being replaced by e-mail. Similar but not identical results are shown by the "average number of activities per day" indicators: daily communication rates decrease significantly for phone and personal meeting,

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[1] The communication diary instructions qualified trips and meetings as follows. For trips: "do **not** count walk trips of under 5 minutes or walk/bike trips within the same campus or shopping center", and for meetings: "do **not** count casual greetings less than one minute long, or interactions with just household members".

and increase for fax, but change very little for the other modes, including e-mail.

TABLE 2
ACTIVITY LEVELS

		Weekday		Weekend	
		Wave 1	**Wave 2**	**Wave 1**	**Wave 2**
Total person-days[2]		275	276	89	88
Total people		91	91	89	88
Phone	No. (%) people w/any inactive days	9 (9.9)	15 (16.5)	14 (15.7)	22 (25.0)
	% of person-days that are inactive	4.7	7.3	15.7	25.0

	Ave. no. activities/day:
	  All person-days
	  Active person-days only
		
		10.75
		11.29
			
			9.51[3]
			10.25
				
				3.88
				4.60
					
					3.91
					5.21

Fax	No. (%) people w/any inactive days	77 (84.6)	76 (83.5)	84 (94.4)	80 (90.9)
	% of person-days that are inactive	61.5	64.9	94.4	90.9

	Ave. no. activities/day:
	  All person-days
	  Active person-days only
		
		0.87
		2.25
			
			1.09
			3.11[3]
				
				0.01
				1.00
					
					0.14
					1.50

E-mail	No. (%) people w/any inactive days	31 (34.1)	32 (35.2)	44 (49.4)	35 (39.8)
	% of person-days that are inactive	22.9	18.5	49.4	39.8

	Ave. no. activities/day:
	  All person-days
	  Active person-days only
		
		11.61
		15.06
			
			11.39
			13.97
				
				4.31
				8.53
					
					5.15
					8.55

Object	No. (%) people w/any inactive days	35 (38.5)	34 (37.4)	51 (57.3)	54 (61.4)
	% person-days that are inactive	17.8	17.8	57.3	61.4

	Ave. no. activities/day:
	  All person-days
	  Active person-days only
		
		7.17
		8.72
			
			6.96
			8.47
				
				2.15
				5.03
					
					1.56
					4.03

----- continued -----					

TABLE 2 (continued)					
Personal meetings	No. (%) people w/any inactive days	29 (31.9)	27 (29.7)	46 (51.7)	37 (42.0)
	% of person-days that are inactive	14.6	16.7	51.7	42.0
	Ave. no. activities/day: All person-days Active person-days only	5.71 6.68	4.65^3 5.58^3	1.99 4.12	1.94 3.35
Trips	No. (%) people w/any inactive days	7 (7.7)	5 (5.5)	15 (16.9)	7 (8.0)
	% of person-days that are inactive	2.9	2.9	16.9	8.0
	Ave. no. activities/day: All person-days Active person-days only	4.11 4.24	4.16 4.29	3.56 4.28	3.31 3.59^3

[2]   In the before wave, two people had data for four weekdays; all others had data for three weekdays and one weekend day (as requested in the instructions). In the after wave, three people had data for four weekdays and all others had data for three weekdays and one weekend day.

[3]   Mean is significantly different from its Wave *1* counterpart at $p \leq 0.10$ (two-sided independent-sample t-test). For the "All person-days" indicator, paired-sample t-tests found the same differences, with $p \leq 0.06$. For the "Active person-days only" indicator, paired-sample t-tests resulted in greatly reduced sample sizes, since often a respondent would be active in one wave but not the other (and thus paired observations would not be available). Hence, the independent-sample t-tests used the data more completely in this case.

The weekend patterns show a more mixed picture. The percent of weekend days on which phone communication and (to a lesser extent) information object delivery occurred declined between waves, whereas the percent of days on which e-mail communication, personal meetings, and trips occurred increased. Average daily weekend communication *rates*, however, remain fairly stable across waves for all modes, with no significant differences found when averaging across all person-days.

The "percent of inactive person-days" indicator corresponds to the "percent immobile" indicator often reported with respect to travel diary data (that is, the percent of the sample not reporting any trips for the day in question), and permits comparison to similar data collected by Zumkeller (1996). For example, in his 1994 sample of 166 Germans, Zumkeller reports a 6% share of

immobile persons with respect to trips. This is reasonably congruent with the 3% share found in our sample for weekdays, with the California sample apparently being slightly more mobile. More marked differences are found for phone, however: Zumkeller reports a 39% "share of immobile persons" with respect to phone, compared to a 5-7% share of inactive person-days in our weekday sample. Several factors could at least partially account for these differences: the proportion of weekdays in Zumkeller's sample is not reported (our sample showed a higher share of "phone inactivity" on weekends, although still no higher than 25%); Zumkeller's diary collected data only on contacts "to a location different to your current location" (so many of his immobile persons may have made/received phone calls to/from co-workers at the same location, and hence would have been classified as "active" in our study); and the fact that the data collection instruments are quite different may have affected the responses in unknown ways. It will be of interest to compare these key indicators across future studies to better understand the extent to which observed differences are artifactual, contextual, temporal, or indicative of genuine cultural disparities in communication patterns.

Since respondents were allowed to choose whether to complete the diary for Sunday - Wednesday (group 0, for the purposes of the following discussion) or for Wednesday - Saturday (group 1), it was necessary to check whether day-of-the-week effects could partially account for any observed changes in communication. If a sizable number of respondents fell into group 0 in wave *1* and changed to group 1 in wave *2* (or conversely), *and* if communication volumes tended to differ systematically between the first part of the work week and the latter part of the work week, then wave effects (true changes in communication levels over time) would be heavily confounded with day-of-week effects.

Only two out of 12 pairs of group means for weekday average numbers of communication activities (wave *1* personal meetings and wave *2* trips) differed significantly between group 0 and group 1. Thus, even if large net shifts between day-of-the-week groups occurred across waves, it would be unlikely to affect the results. As for group stability across waves, a similar number of respondents fell into group 0 in each wave (54 in wave *1* and 57 in wave *2*), but they were by no

means mostly the same respondents each time. Most importantly, nearly as many respondents switched from group 0 to 1 (24) as switched in the opposite direction (27). Hence, it seems reasonable to conclude that any systematic differences seen between the two waves can be attributed to a true wave effect and not to wholesale shifts from one day-of-the-week group to another.

4. STRUCTURAL EQUATION RESULTS

The aggregate results presented in the previous section offer a useful overview of net impacts. However, a disaggregate analysis may reveal patterns that "wash out" in the aggregate, and will provide more insight into specific relationships of one communication mode to the others. In this section, we present disaggregate structural models of these relationships. In view of the differences seen in Table 2, and our belief that different processes may govern communication generation and mode choice on weekends than during the work week, separate models were estimated for weekdays (Monday - Friday) and for weekends.

For the sake of brevity, we present only the results for weekday communications in the body of this report. Weekend results are provided in the appendix, together with the correlations and standard deviations for the variables in both data sets, in keeping with acceptable practice for structural equations modeling (Hoyle and Panter, 1995). The results were less interpretable for the weekend models than for the weekday models, suggesting that there may be considerably more unexplained variability in communication patterns on weekends than on weekdays. It would be of interest to estimate a combined weekday - weekend model to identify potential interactions across day type (for example, increases in weekday trips may be compensated for by decreases in weekend trips). Unfortunately, however, the sample size of 91 does not support the estimation of a 12-equation system with dozens of parameters. Such an analysis awaits replication of this methodology on a larger sample.

In this exploratory research, a number of different model specifications were tested, the general hypothesis (as illustrated by Figure 1) being that any lagged endogenous variable (and any

exogenous variable) could potentially affect any other endogenous variable. Because of the small sample size and the exploratory nature of the study, a p-value of 0.1 was used as the cutoff for significance. In the "best" final specifications presented here, included variables have a significance level of 0.1 or lower, except in a few cases where excluding an insignificant variable degraded the interpretability of the rest of the model. Variables that were tested for inclusion but not found to be significant in the final models included gender, a dummy variable for full-time employment status, number of full-time workers in the household, number of vehicles available to the household, commute time, and computer experience. Income was also tested in some models, but missing data on that variable would have decreased the sample size to 83, which was considered unacceptable. Education had slightly fewer missing cases but was not used for the same reason.

For the weekday data, we present two models: a direct effects model – that is, one containing both exogenous and lagged endogenous variables, and an endogenous-only effects model – that is, one in which the only explanatory variables are the lagged endogenous variables, plus the elapsed time variable and the seasonal dummies (only one of which was significant in any equation). This latter model represents an $X \oslash Y_1 \oslash Y_2$ structure (where X represents the set of exogenous variables and Y_i represents endogenous variables at time i) rather than a structure in which X and Y_1 simultaneously act on Y_2 but not on each other. The $X \oslash Y_1 \oslash Y_2$ structure may be more appropriate in this situation, in which the exogenous variables are not time-dependent and are measured at or before the wave 1 endogenous variable measurement time.

Prior to estimating the models, the data were checked for univariate and multivariate normality. Significant departures from normality were found. For the variables in the direct effects model, Mardia's measure of multivariate kurtosis was 79.33, with a critical ratio of 14.10 (a critical ratio above 1.96 would signify departure from multivariate normality with 95% confidence). The same measure for the variables in the endogenous-only effects model was 84.75, with a critical ratio of 19.10. These results led us to transform variables as necessary to achieve approximate normality (West, *et al.*, 1995). Natural log (of the original variable plus one, to avoid taking the

log of zero) and square root transformations sufficed, and Mardia's measure for the transformed variables used in the direct effects model was 0.95, with a critical ratio of 0.17. The same measure for the variables used in the endogenous-only effects model was 5.87, with a critical ratio of 1.32.

Turning first to the direct effects model shown in Table 3, several patterns are immediately apparent. The own-mode coefficients are all positive as expected (high levels of communication by mode j at time 1 are associated with high levels of the same mode at time 2) and (except for communication by information object) strongly significant. The elapsed time variable is also always positive and, in four out of six cases, highly significant. These results indicate net generation of communication activities over time.

	$\ln(\text{Phone}_2)$	$\text{sq}(\text{Fax}_2)$	$\ln(\text{E-mail}_2)$	$\ln(\text{Object}_2)$	$\ln(\text{Personal meetings}_2)$	$\ln(\text{Trips}_2)$
$\ln(\text{Phone}_1)$	0.56 (6.62)					
$\text{sq}(\text{Fax}_1)$		0.45 (4.18)		0.29 (1.86)		
$\ln(\text{E-mail}_1)$			0.45 (5.05)			
$\ln(\text{Object}_1)$						
$\ln(\text{Personal meetings}_1)$		-0.16 (-1.98)			0.50 (7.51)	
$\ln(\text{Trips}_1)$					0.23 (1.85)	0.38 (3.94)
$\text{sq}(\text{Elapsed weeks})$	0.12 (3.69)	0.085 (3.78)	0.24 (5.88)	0.10 (1.18)	0.047 (1.34)	0.17 (5.94)
Fall dummy variable			-0.36 (-2.00)			
Winter dummy variable					0.26 (1.88)	0.24 (2.21)
Manager dummy variable	0.26 (1.53)	0.25 (1.45)				
$\ln(\text{Age})$				0.45 (1.66)		
$\ln(\text{Household size})$	0.13 (1.17)					

[4]   Blank cells in this table represent "structural zeroes", that is coefficients constrained to be zero in the model. Some insignificant ($p < 0.1$) coefficients are retained, only when doing so improves overall interpretability. "Ln" refers to the natural log and "sq" to the square root transformations.

The interpretation of the magnitude of the elapsed time coefficient is made more difficult by the non-linear transformations of both elapsed time and the dependent variables, with the implication of a diminishing rather than constant marginal impact of an additional unit (week) of elapsed time on (the transformed) daily average communication rate. However, by reversing the transformations at sample mean values, it can be seen that the passage of another week (all else equal) would result in an average addition of about 0.14 e-mail messages per day and 0.016

personal meetings per day. It is interesting but not surprising that the newest (and in many ways most convenient) mode of communication – e-mail – is the most rapidly growing one, and that the oldest (and potentially most time-consuming) one – personal meetings – is the slowest growing. However, it is intriguing that trips have the second-highest rate of growth: the passage of another week at the sample mean number of weeks and of ln(trips) would result in an average addition of about 0.07 trips per day.

Only three cross-lagged effects are significant at $p \leq 0.1$: personal meetings have a negative effect on faxes (substitution), whereas faxes have a positive effect on information objects and trips have a positive effect on personal meetings (complementarity). In this direct effects model, then, the net generation of communication activities is combined with a few cross-mode effects which are mixed substitution and complementarity.

Several exogenous variables also appear in the direct effects model. Age has a positive effect on number of information objects sent/received. Being a manager (true for 14.3% of the estimation sample) has a marginally positive effect on phone calls ($p = 0.13$) and faxes ($p = 0.15$) made/sent/received, both of which are logical. Wave *1* data collected in the winter quarter (January - March), showed a stronger impact on wave *2* personal meetings and trips than did wave *1* data collected in the base summer quarter. This may reflect a post-holiday dip in wave *1* personal meetings and trips (both business and social), resulting in larger differences between wave *1* and wave *2*. Conversely, the fall dummy was negatively significant in the equation for e-mail, suggesting that fall e-mail activity was elevated over the summer base, which may have been affected by vacations.

Turning to the endogenous-only effects model of Table 4, an even stronger picture of comple-mentarity emerges. Again, all own-mode effects except for information object ($p = 0.07$) are positive and highly significant, and similarly for all elapsed time coefficients except for the personal meetings equation. This time, however, several more cross-mode effects are significant (which is not surprising since other exogenous variables have been removed), and all significant cross-mode effects are positive except for the weak impact of faxes on personal meetings ($p = 0.13$) – the counterpart to the negative effect seen in the first model. Specifically, phone has a positive impact on information objects; information objects have a positive impact on phone and

personal meetings; and personal meetings and trips each have a positive impact on the other. Collectively, there are at least marginally significant cross-mode effects in one direction or the other and of one sign or the other, among all three main modes of communication – clearly illustrating their interdependence. For this model, however, the predominant effects are net generation and cross-mode complementarity.

Various fit measures for the two models are presented in Table 5 (see, e.g., Arbuckle, 1997; Hoyle, 1995; and the references cited therein for a more complete discussion of fit measures). Both models fit the data well. On every measure, the endogenous-only effects model of Table 4 is superior to the direct effects model of Table 3, lending support to the previous suggestion that the conceptual relationships implied by the endogenous-only effects model are more appropriate for this empirical context.

TABLE 4
ENDOGENOUS-ONLY EFFECTS MODEL – WEEKDAY (N = 91)[5]
(Numbers in parentheses are t-statistics)

	$\ln(\text{Phone}_2)$	$\text{sq}(\text{Fax}_2)$	$\ln(\text{E-mail}_2)$	$\ln(\text{Object}_2)$	$\ln(\text{Personal meetings}_2)$	$\ln(\text{Trips}_2)$
$\ln(\text{Phone}_1)$	0.55 (6.55)			0.29 (2.24)		
$\text{sq}(\text{Fax}_1)$		0.45 (4.21)			-0.13 (-1.50)	
$\ln(\text{E-mail}_1)$			0.52 (5.90)			
$\ln(\text{Object}_1)$	0.25 (3.49)			0.20 (1.81)	0.16 (2.69)	
$\ln(\text{Personal meetings}_1)$					0.57 (7.11)	0.17 (2.83)
$\ln(\text{Trips}_1)$					0.22 (2.88)	0.32 (3.57)
$\text{sq}(\text{Elapsed weeks})$	0.086 (2.73)	0.055 (3.66)	0.17 (4.77)	0.11 (2.24)		0.14 (6.01)
Winter dummy variable			0.60 (2.97)		0.23 (1.75)	0.24 (2.27)

[5]   Blank cells in this table represent "structural zeroes", that is coefficients constrained to be zero in the model. Some insignificant ($p < 0.1$) coefficients are retained, only when doing so improves overall interpretability. "Ln" refers to the natural log and "sq" to the square root transformations.

TABLE 5
COMPARISON OF MEASURES OF FIT (N = 91)

	Direct effects model	Endogenous-only effects model
Degrees of freedom	57	34
χ^2: measures discrepancy between observed and model-implied covariances; the smaller the better	56.476	19.825
p-value: for H_0 that the model reproduces the observed covariances well; the larger (closer to one) the better	0.495	0.975
χ^2/d.f.: values close to one and below indicate a good fit; the larger the worse	0.991	0.583
Normed Fit Index: proportion of baseline (independence) model χ^2 explained by the model of interest; varies between 0 and 1, with 1 being best	0.982	0.992
Relative Fit Index: NFI corrected for degrees of freedom; values close to one indicate a good fit	0.947	0.976
Incremental Fit Index: the incremental improvement of the model of interest over the baseline (independence) model; values close to 1 indicate a good fit	1.000	1.006
Comparative Fit Index: assumes a noncentral χ^2 distribution for the baseline model discrepancy; values close to one indicate a good fit	1.000	1.000
Akaike Information Criterion: balances discrepancy against complexity; in comparing two models, the smaller the better	320.476	189.825
Browne - Cudeck Criterion: penalizes complexity more heavily than the AIC; in comparing two models, the smaller the better	391.124	223.825

It is of interest to analyze the estimated cross-equation correlations of the error terms in the model. These are presented in Table 6. The results are quite similar for both the direct effects model and the endogenous-only effects model, and quite interpretable. The largest correlation (0.57) is between the equations for personal meetings and trips, reflecting the conceptual overlap between those two variables: the implication, not surprisingly, is that much of the unexplained variation in these two variables is due to sources common to both. At the other end of the spectrum, the smallest correlations (-0.06 - 0.07) are those between the unobserved variables for the e-mail equation and those for all other equations – reflecting the unique nature of e-mail among the communication modes studied here. The other correlations lie distinctly between these two extremes, indicating a moderate level of commonality among unobserved variables for these equations.

TABLE 6
ESTIMATED CORRELATIONS OF DISTURBANCE TERMS – WEEKDAY (N = 91)

DIRECT EFFECTS MODEL						
	$\ln(\text{Phone}_2)$	$\text{sq}(\text{Fax}_2)$	$\ln(\text{E-mail}_2)$	$\ln(\text{Object}_2)$	$\ln(\text{Personal meetings}_2)$	$\ln(\text{Trips}_2)$
$\ln(\text{Phone}_2)$	1.00					
$\text{sq}(\text{Fax}_2)$	0.29	1.00				
$\ln(\text{E-mail}_2)$	0.05	-0.03	1.00			
$\ln(\text{Object}_2)$	0.35	0.28	0.05	1.00		
$\ln(\text{Personal meetings}_2)$	0.30	0.24	0.07	0.38	1.00	
$\ln(\text{Trips}_2)$	0.28	0.16	0.03	0.24	0.56	1.00
ENDOGENOUS-ONLY EFFECTS MODEL						
	$\ln(\text{Phone}_2)$	$\text{sq}(\text{Fax}_2)$	$\ln(\text{E-mail}_2)$	$\ln(\text{Object}_2)$	$\ln(\text{Personal meetings}_2)$	$\ln(\text{Trips}_2)$
$\ln(\text{Phone}_2)$	1.00					
$\text{sq}(\text{Fax}_2)$	0.25	1.00				
$\ln(\text{E-mail}_2)$	-0.04	-0.06	1.00			
$\ln(\text{Object}_2)$	0.32	0.26	-0.01	1.00		
$\ln(\text{Personal meetings}_2)$	0.25	0.21	-0.01	0.36	1.00	
$\ln(\text{Trips}_2)$	0.25	0.14	-0.01	0.27	0.57	1.00

5. DISCUSSION

This study applies disaggregate longitudinal structural equations modeling to analyze the inter-relationships among various modes of communication at the individual level. Net generation of communication was found over a six-month period, and the predominant cross-mode impact appears to be complementarity rather than substitution. These results are consistent with other disaggregate, but cross-sectional, studies of these relationships. Zumkeller (1996) concludes that "the complementary factor of the interrelationship between travel and communication is much stronger than the substitutional one", since high levels of tripmaking were found to be associated with high levels of communication activity. A KMPG (1997) study of Dutch respondents found that heavy users of information technology traveled about the same amount overall as an other-wise similar comparison group, but the heavy IT users had considerably greater work-related travel.

It is interesting to note that the model results of generation and complementarity would not necessarily have been expected based on an examination of the aggregate data shown in Table 2 alone. Adding the average number of activities per day across the six communication modes studied shows a slight decline for weekdays, from 40.22 "total" daily communications in wave *1* to 37.76 in wave *2* (the total for weekends increases negligibly, from 15.90 to 16.01). Declines occurred in four of the six individual categories (for weekdays), although as indicated earlier, for only two of those, phone and personal meetings, were the changes statistically significant (whereas neither of the increases in the remaining two categories was significant). Clearly the models, by accounting for disaggregate-level interactions among all variables, are able to identify relationships that are not apparent at a purely aggregate level.

Several aspects of the analysis presented here point to the special character of e-mail among the communication modes studied. Especially for weekdays, the aggregate data show that the per-cent of person-days on which e-mail communication took place increased across waves, while the same indicator decreased for phone, fax, and personal meetings. The magnitudes of the elapsed time coefficients in the structural equations models show that, all else equal, e-mail is the fastest-growing mode among the six studied – increasing almost twice as fast (at mean values) as the second-fastest-growing mode in the direct effects model. Also, the cross-equation error term correlations show that the unobserved variables affecting choice of e-mail are relatively distinct

from those affecting other communication modes. These results are doubtless influenced by the context in which the data were collected (that is, adoption of a communication system facilitating access to the Internet); it would be of interest to examine whether they hold under more general conditions. We speculate that e-mail will continue to show relatively rapid growth and distinct influences, due to its ease of use and increasing ubiquity.

The findings of generation and complementarity will be of interest to transportation planners. Given the conceptual nature of the relationships between telecommunications and travel described here and elsewhere (e.g. Mokhtarian, 1990), and the mounting empirical evidence supporting a predominant effect of complementarity (see Mokhtarian and Salomon, 1997), it appears unlikely that telecommunications will noticeably reduce travel at a system level. In fact, it is telling that, while the fastest-growing communication mode in this sample was the newcomer e-mail, the second-fastest-growing mode (seen by the magnitudes of the elapsed time coefficients in both models) was travel. Clearly, trips are not giving way to telecommunications.

We believe that the longitudinal structural equations modeling approach holds considerable promise as a way to analyze the multi-directional relationships among different means of communication. In particular, it offers the ability to simultaneously model both communication generation and mode "choice", so to speak, and therefore to identify the net effects of what may be counteracting tendencies – e.g. substitution of phone by e-mail (although such an effect was not empirically observed in the final models presented here) simultaneously with generation of new communication in both modes. As such, we see this approach as a logical way of breaking out of the narrowly-focused, unidirectional analyses of the impacts of a particular telecommunications application (such as telecommuting) on travel which have been the norm to date. The early results presented here support the speculation offered in the introduction – that the narrowly-focused studies are more likely than this broader approach to find a substitution effect, simply because complementarity effects may be more indirect and longer-term.

As initially applied here, however, the approach had several limitations. One obvious limitation was the small sample size, which reduced the precision with which effects could be estimated, and precluded more sophisticated models of interaction. Interactions of interest include those (1) across day type (weekday versus weekend); (2) among finer categories of submodes (e.g.,

distinguishing fixed location phone calls from mobile phone calls); (3) between sent versus received communications; and (4) using other distinctions identified within the data collection instrument (e.g., location of the respondent – work, home, other – and time period – morning, afternoon, evening – when the communication occurred). This limitation is presumably easily remedied in future studies.

More substantively, simply counting the number of communication events in each category is a rather crude measure of activity. No indication of the total time spent in each communication mode was available, so (as mentioned in Section 2) findings of a net increase in number of communications may not translate to an increase in time spent on communication. More subtly, there may be cross-mode complementarity when number of events is the measure, but substitution when time is the measure (for example, one may replace a single trip with several phone calls and an object delivery, but still spend less total time in communication than the trip would have involved).

Using number of events rather than time as the indicator of communication activity is analogous, in a purely travel context, to analyzing number of trips rather than distance traveled: it is useful as far as it goes, but incomplete. Thus, applying the methodology described here to modeling time spent in each communication mode is an obvious improvement (although not perfect, as argued in Section 2), and one which is relatively easily accomplished (at the cost of an increased reporting burden on the respondent).

Another shortcoming of the approach as applied here is that inference of causality is limited and indirect. With only two waves, six months apart, wave *1* measures cannot be assumed to "cause" wave *2* measures in the strictest sense of the word. As discussed earlier, however, resolving this issue is not straightforward, theoretically or practically. Nevertheless, even the observation that wave *1* measures are "associated with" wave *2* effects is worth making. One context in which causal inferences would be stronger is in a before-and-after study involving some type of intervention, with a control group not receiving the intervention. An example might be analyzing the communication and travel impacts of a new teleshopping service by comparing before-and-after relationships of those who receive the service to an otherwise similar group of respondents who do not receive the service. Future application of this methodology in such a

context would be valuable.

Obtaining richer disaggregate data on communication activities presents some formidable measurement challenges, as we have outlined here. Nevertheless, they are challenges worth tackling, in return for the improved insight into telecommunications - travel relationships which is sure to result.

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APPENDIX

ADDITIONAL ANALYSIS DETAILS:

CORRELATIONS AND STANDARD DEVIATIONS OF MODEL VARIABLES

AND

WEEKEND MODEL RESULTS

TABLE A-1
CORRELATION MATRIX
WEEKDAY (N=91)

	Lnawkphb	Sqawkfxb	Lnawkelb	Lnawkob	Lnawkpmb	Lnawktrb	Lnawkpha	Sqawkfxa	Lnawkela	Lnawkoa	Lnawkpma	Lnawktra	Fallb	Winterb	Sqlength	Manager	Lnage	Lnhhsize
Lnawkphb	1.000																	
Sqawkfxb	0.441	1.000																
Lnawkelb	-0.049	0.139	1.000															
Lnawkob	0.324	0.304	0.251	1.000														
Lnawkpmb	0.178	0.168	0.273	0.418	1.000													
Lnawktrb	-0.013	0.051	0.089	0.120	0.329	1.000												
Lnawkpha	0.548	0.283	0.055	0.432	0.240	0.040	1.000											
Sqawkfxa	0.219	0.381	0.031	0.184	-0.056	0.039	0.328	1.000										
Lnawkela	0.001	0.111	0.533	0.217	0.139	-0.001	0.047	-0.011	1.000									
Lnawkoa	0.219	0.174	0.019	0.221	0.081	0.043	0.385	0.309	0.030	1.000								
Lnawkpma	0.099	0.059	0.191	0.377	0.633	0.300	0.320	0.114	0.116	0.325	1.000							
Lnawktra	-0.069	0.057	0.123	0.087	0.355	0.371	0.173	0.104	0.046	0.226	0.618	1.000						
Fallb	0.078	-0.006	-0.036	0.019	0.073	0.186	0.059	-0.037	-0.168	0.011	0.055	0.116	1.000					
Winterb	-0.036	-0.021	-0.370	-0.048	-0.124	-0.159	-0.001	0.033	-0.101	0.018	0.073	-0.071	-0.460	1.000				
Sqlength	-0.007	0.005	0.374	0.018	0.133	0.147	-0.034	-0.029	0.165	-0.046	-0.069	0.061	0.269	-0.922	1.000			
Manager	0.284	0.263	0.031	0.245	0.232	0.039	0.290	0.221	0.042	0.110	0.158	-0.039	0.063	-0.124	0.128	1.000		
Lnage	0.092	0.149	0.135	0.231	0.299	-0.086	0.110	0.106	0.082	0.117	0.193	-0.007	-0.144	-0.027	0.094	0.127	1.000	
Lnhhsize	0.131	0.201	-0.107	-0.116	0.044	0.029	0.073	0.049	-0.040	-0.141	0.029	-0.016	-0.007	0.154	-0.197	-0.030	-0.146	1.000
S.d	0.660	0.557	1.051	0.851	0.752	0.447	0.712	0.636	0.973	0.912	0.747	0.465	0.501	0.401	0.857	0.352	0.210	0.507

	Lnawephb	Sqawefxb	Lnaweelb	Lnaweob	Lnawepmb	Sqawetrb	Lnawepha	Sqawefxa	Lnaweela	Lnaweoa	Lnawepma	Sqawetra	Winterb	Sqlength	Manager	Profess	Lnage	Gender	Lnhhsize
nawephb	1.000																		
qawefxb	0.387	1.000																	
naweelb	0.129	0.171	1.000																
naweob	0.335	0.324	0.167	1.000															
nawepmb	0.205	-0.049	0.080	0.180	1.000														
qawetrb	-0.027	-0.123	-0.042	0.086	0.258	1.000													
nawepha	0.544	0.249	0.164	0.365	0.160	-0.158	1.000												
qawefxa	0.262	0.449	0.148	0.224	-0.076	-0.072	0.354	1.000											
naweela	0.316	0.107	0.549	0.201	0.178	-0.248	0.272	-0.015	1.000										
naweoa	0.205	0.158	0.260	0.477	0.290	0.082	0.407	0.184	0.194	1.000									
nawepma	0.052	-0.074	0.086	0.298	0.649	0.283	0.149	-0.018	0.052	0.343	1.000								
qawetra	0.074	-0.068	0.196	0.055	0.255	0.496	0.109	-0.051	0.083	0.163	0.369	1.000							
Winterb	-0.042	0.267	-0.294	0.102	0.054	-0.175	0.001	0.009	0.032	-0.003	0.055	-0.143	1.000						
qlength	-0.008	-0.277	0.278	-0.106	-0.071	0.152	-0.047	-0.025	0.038	0.008	-0.127	0.092	-0.922	1.000					
Manager	0.274	0.131	0.013	0.252	0.107	0.071	0.234	0.374	-0.050	0.201	0.104	0.005	-0.124	0.128	1.000				
rofess	-0.076	0.042	0.110	-0.101	0.054	-0.145	-0.147	-0.197	0.293	-0.059	-0.029	-0.113	0.114	-0.052	-0.582	1.000			
nage	0.141	0.183	0.086	0.108	0.356	0.084	0.188	0.104	0.127	0.349	0.264	0.146	-0.027	0.094	0.127	0.137	1.000		
iender	0.075	0.093	0.246	-0.184	0.003	-0.052	0.005	0.011	0.071	0.062	-0.109	-0.041	-0.109	0.165	-0.170	0.285	0.148	1.000	
nhhsize	0.062	0.095	-0.099	0.074	0.050	-0.074	0.140	0.199	-0.100	0.033	0.148	-0.093	0.154	-0.197	-0.030	-0.132	-0.146	0.059	1.000
s.d.	0.861	0.737	1.265	0.966	0.826	0.550	0.740	0.877	1.139	0.832	0.816	0.537	0.401	0.857	0.352	0.473	0.210	0.477	0.507

TABLE A-3

DIRECT EFFECTS MODEL – WEEKEND (N = 91)[6]
(Numbers in parentheses are t-statistics)

	$\ln(\text{Phone}_2)$	$\text{sq}(\text{Fax}_2)$	$\ln(\text{E-mail}_2)$	$\ln(\text{Object}_2)$	$\ln(\text{Personal meetings}_2)$	$\text{sq}(\text{Trips}_2)$
$\ln(\text{Phone}_1)$	0.49 (7.23)					
$\text{sq}(\text{Fax}_1)$		0.47 (4.85)				
$\ln(\text{E-mail}_1)$			0.51 (7.28)			0.09 (2.60)
$\ln(\text{Object}_1)$				0.33 (5.38)		
$\ln(\text{Personal meetings}_1)$					0.59 (7.72)	
$\text{sq}(\text{Trips}_1)$			-0.37 (-2.32)		0.22 (1.88)	0.55 (6.66)
$\text{sq}(\text{Elapsed weeks})$	0.16 (4.91)	0.04 (1.91)	0.23 (3.18)			0.13 (3.49)
Winter dummy variable			0.84 (3.78)			0.22 (1.95)
Manager dummy variable		0.78 (4.41)				
Professional dummy variable			0.44 (2.75)			
Gender					-0.18 (-4.89)	
$\ln(\text{Age})$				1.10 (3.65)		
$\ln(\text{Household size})$	0.20 (1.77)					

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[6] Blank cells in this table represent "structural zeroes", that is coefficients constrained to be zero in the model. Some insignificant ($p < 0.1$) coefficients are retained, only when doing so improves overall interpretability. "Ln" refers to the natural log and "sq" to the square root transformations.

TABLE A-4
ENDOGENOUS-ONLY EFFECTS MODEL – WEEKEND (N = 91)[7]

(Numbers in parentheses are t-statistics)

	ln(Phone$_2$)	sq(Fax$_2$)	ln(E-mail$_2$)	ln(Object$_2$)	ln(Personal meetings$_2$)	sq(Trips$_2$)
ln(Phone$_1$)	0.41 (5.67)		0.32 (3.24)		-0.18 (-2.68)	
sq(Fax$_1$)		0.50 (4.80)				
ln(E-mail$_1$)			0.50 (6.85)	0.09 (1.45)		0.10 (2.59)
ln(Object$_1$)	0.16 (2.41)			0.38 (5.07)	0.22 (3.39)	
ln(Personal meetings$_1$)				0.22 (2.58)	0.61 (8.09)	
sq(Trips$_1$)			-0.44 (-2.83)		0.16 (1.97)	0.53 (6.28)
sq(Elapsed weeks)	0.17 (5.46)	0.06 (3.11)	0.18 (2.43)	0.09 (2.56)		0.11 (3.24)
Fall dummy variable					0.24 (1.89)	0.18 (1.70)
Winter dummy variable	0.30 (1.99)		0.84 (3.67)			0.32 (2.57)

[7]   Blank cells in this table represent "structural zeroes", that is coefficients constrained to be zero in the model. Some insignificant ($p < 0.1$) coefficients are retained, only when doing so improves overall interpretability. "Ln" refers to the natural log and "sq" to the square root transformations.

TABLE A-5

COMPARISON OF MEASURES OF FIT – WEEKEND (N = 91)

	Direct effects model	Endogenous-only effects model
Degrees of freedom	63	35
χ^2: measures discrepancy between observed and model-implied covariances; the smaller the better	321.213	31.710
p-value: for H_0 that the model reproduces the observed covariances well; the larger (closer to one) the better	0.000	0.628
χ^2/d.f.: values close to one and below indicate a good fit; the larger the worse	5.099	0.906
Normed Fit Index: proportion of baseline (independence) model χ^2 explained by the model of interest; varies between 0 and 1, with 1 being best	0.911	0.988
Relative Fit Index: NFI corrected for degrees of freedom; values close to one indicate a good fit	0.732	0.960
Incremental Fit Index: the incremental improvement of the model of interest over the baseline (independence) model; values close to 1 indicate a good fit	0.927	1.001
Comparative Fit Index: assumes a noncentral χ^2 distribution for the baseline model discrepancy; values close to one indicate a good fit	0.924	1.000
Akaike Information Criterion: balances discrepancy against complexity; in comparing two models, the smaller the better	613.213	231.710
Browne - Cudeck Criterion: penalizes complexity more heavily than the AIC; in comparing two models, the smaller the better	696.641	274.953

TABLE A-6

ESTIMATED CORRELATIONS OF DISTURBANCE TERMS – WEEKEND (N = 91)

DIRECT EFFECTS MODEL						
	ln(Phone$_2$)	sq(Fax$_2$)	ln(E-mail$_2$)	ln(Object$_2$)	ln(Personal meetings$_2$)	sq(Trips$_2$)
ln(Phone$_2$)	1.00					
sq(Fax$_2$)	0.21	1.00				
ln(E-mail$_2$)	0.06	-0.13	1.00			
ln(Object$_2$)	0.26	0.08	0.01	1.00		
ln(Personal meetings$_2$)	0.17	0.07	-0.09	0.15	1.00	
sq(Trips$_2$)	0.21	-0.01	0.15	0.08	0.24	1.00

ENDOGENOUS-ONLY EFFECTS MODEL						
	ln(Phone$_2$)	sq(Fax$_2$)	ln(E-mail$_2$)	ln(Object$_2$)	ln(Personal meetings$_2$)	sq(Trips$_2$)
ln(Phone$_2$)	1.00					
sq(Fax$_2$)	0.26	1.00				
ln(E-mail$_2$)	0.00	-0.19	1.00			
ln(Object$_2$)	0.29	0.11	-0.05	1.00		
ln(Personal meetings$_2$)	0.13	0.09	-0.07	0.16	1.00	
sq(Trips$_2$)	0.21	-0. 02	0.11	0.09	0.25	1.00