IMPACTS OF HOME-BASED TELECOMMUTING ON VEHICLE-MILES TRAVELED: A NATIONWIDE TIME SERIES ANALYSIS

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by

Sangho Choo
Department of Civil and Environmental Engineering
and
Institute of Transportation Studies
University of California
Davis, California
phone: 530-754-7421 fax: 530-752-6572
cshchoo@ucdavis.edu

Patricia L. Mokhtarian
Department of Civil and Environmental Engineering
and
Institute of Transportation Studies
University of California
Davis, California
phone: 530-752-7062 fax: 530-752-7872
plmokhtarian@ucdavis.edu

and

Ilan Salomon
Leon J. and Alyce K. Ell Professor of Environmental Studies
Department of Geography
The Hebrew University of Jerusalem
Jerusalem 91905 Israel
phone: 972-2-5883345 fax: 972-2-5820549
msilans@mscc.huji.ac.il

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IMPACTS OF HOME-BASED TELECOMMUTING ON VEHICLE-MILES TRAVELED: A NATIONWIDE TIME SERIES ANALYSIS

by Sangho Choo, Patricia L. Mokhtarian, and Ilan Salomon

EXECUTIVE SUMMARY

Study Background and Purpose

Teleworking is defined for this report as working at home or a location closer to home than the regular workplace, using information and communication technology (ICT) to support productivity and communication with the supervisor, co-workers, clients, and so on. We distinguish two main types of teleworkers: salaried employees of an organization, called telecommuters, and primary home-based business workers. In view of the ambiguity of the transportation impacts of home-based business work, the difficulty in obtaining reliable data on its nature and extent, and the limited time frame of this study, we focus only on salaried telecommuters here. We do not count after-hours work as telecommuting, if the employee still spends a full day at the regular workplace. We also focus only on home-based telecommuting, since center-based telecommuters probably number only in the hundreds nationwide.

A number of small-scale empirical studies have established the short-term transportation (and air quality) benefits of telecommuting at the disaggregate level, finding that vehicle-miles traveled are substantially reduced for those who telecommute, on days that they telecommute, for as long as they telecommute. The question is whether that impact "scales up" to a systemwide level. It has been suggested that it will not, in view of the relatively small amounts of telecommuting occurring today, the relatively slow growth that can be expected as the phenomenon matures and as attrition continues to occur, and the likelihood of long-term indirect impacts partly counteracting the short-term direct savings. Nevertheless, to our knowledge an aggregate study of the impact of teleworking on transportation has not previously been conducted, and that is the purpose of the present study.

Substitution of telecommunications for travel is the impact most desired from a public policy perspective, but it is not the only possibility. In particular, telecommunications may also have a complementary relationship to travel, and similar impacts of travel on telecommunications may occur as well. To fully assess the interactive relationships between these two indicators, measures of complete amounts of both transportation and telecommunications, and models allowing both directions of causality, are needed. However, such a bi-directional structural equations model with aggregate time series data is beyond the scope of the current project. In the present study, we focus on a single direction of causality and a subset of all telecommunications activity, to explore the impact of home-based telecommuting on vehicle-miles traveled (VMT). The single-equation results presented here are inevitably subject to the endogeneity bias that occurs when explanatory variables in a single equation are actually endogenous to the system of interest rather than exogenous influences on the dependent variable of the equation. With that caveat in mind, however, the tentative results that can be obtained here are still of interest for the new insight they may be able to provide into the relationship between telecommuting and travel at the aggregate level – in particular to see whether the substitution effect observed in the disaggregate studies can be replicated.

Data Used in the Study

This study estimates the impact of telecommuting on personal transportation through a multivariate time series analysis of aggregate nationwide data spanning 1966-1999 for all variables except telecommuting, and 1988-1998 for telecommuting. Three dependent variables were modeled, in direct and per-capita forms: ground vehicle-miles traveled (VMT), airline passenger-miles traveled (PMT), and the sum of those two variables, loosely referred to as "total miles traveled". The analysis was conducted in two stages. In the first stage (after ensuring that all series were stationary through first-differencing and log transformations), each dependent variable (1966-1999) was modeled as a function of conventional variables representing economic activity (e.g. GDP, employment, disposable income), the cost of transportation (e.g. gasoline price, fuel efficiency, CPI for transportation), transportation supply (lane-miles of roadways), and demographics (e.g. population, household size, licensed drivers, number of personal vehicles). A total of 15 explanatory variables were allowed to enter the first-stage models. In the second stage, the residuals of the first stage (1988-1998) were modeled as a function of the number of telecommuters.

The study necessarily relied on secondary data sources. In particular, we addressed some of the key issues (such as definition, quality, and quantity) associated with measuring telecommuting, and then assessed the available data. Although none of the telecommuting data sources is entirely satisfactory, the necessity of having data measured reasonably consistently over a series of years dictated the choice of data for this study. The chosen series, based on data collected by a single individual for several different market research firms across time, represents the longest series of data available on number of telecommuters, with estimates published for each year between 1988 and 1998. The estimates are based on 2,000 – 2,500 randomly-selected households interviewed by telephone each year. However, it should be stressed that these numbers, based as they are on small samples that must rely on the proper weighting in order to be representative, are in our opinion subject to a great deal of uncertainty. From various considerations, it is likely that the data used here overestimate the true number of telecommuters.

We assess the change in annual VMT per telecommuter, which can then be translated to a change in VMT per telecommuting occasion based on an assumption about the average telecommuting frequency (and hence the number of occasions in a year). Considering the stable average frequencies of telecommuting over time found in the literature, as well as the lack of complete information on frequency for each year in the sample, we assume the average frequency of telecommuting to be constant across the period of study. The results are presented for two such assumptions: 50 occasions per year (representing a frequency of about once a week, not including vacation weeks), and 75 occasions per year (about 1.5 days a week).

Results

Tables ES-1 and ES-2 (19 and 20 in the text) summarize the coefficients and telecommuting effects (in 1998) for the preferred models of each of the three dependent variables analyzed in this study. We briefly discuss the key results for each variable in turn.

Ground VMT per capita: The first stage model has an adjusted R^2 of 0.65. The five significant variables (besides the constant term) represent economic activity and the cost of transportation, with GDP per capita and miles per gallon having the expected positive signs, and gasoline price and the combined effect of CPI-all and CPI-transportation having the expected negative signs. The second stage model has an adjusted R^2 of 0.27, and the coefficient for number of telecommuters is significant and negative, suggesting that telecommuting does measurably reduce VMT.

When the amount of that reduction is quantified, however, concerns regarding its plausibility emerge. Using the estimated coefficient of telecommuting directly, the estimated impact on VMT in 1998 constitutes a reduction of 2.12% of the total. This translates to 66 miles eliminated per telecommuting occasion on the assumption of 50 occasions per year, and 44 miles per occasion at an assumed 75 occasions per year. Even the lower number of 44 miles seems unrealistically high compared to benchmark data on average commute lengths and average daily VMT. Thus, we present the VMT reductions estimated by the 95% and 90% confidence intervals on the coefficient of telecommuting, and consider the true mean impact more likely to lie in the upper halves of those intervals. The 95% confidence interval on the coefficient encloses the value zero, meaning that with that standard, we cannot reject the null hypothesis that telecommuting has no impact on VMT. On the other hand, the 90% confidence interval does not include zero.

Taken together, these results can be simply summarized as follows:

- Assuming the specified models are the correct ones, we can be 90% confident that telecommuting reduces VMT (by an amount as little as 0.34% of the observed VMT in 1998), but not 95% confident.
- The amount of that reduction is most likely small, falling somewhere between a 2% reduction in VMT and essentially no change in VMT.

These results are very consistent with those of a previous study (Mokhtarian, 1998) estimating the aggregate impact of telecommuting on VMT, using data and methods completely independent of the present study. Applying the "future case" scenario assumptions[*] of that study – a scenario consistent with the level of telecommuting reported for 1998 – to the 15.7 million telecommuters estimated in 1998, yields an estimated 19,329.84 million vehicle-miles/year saved due to telecommuting. This constitutes 0.79% of the 2,428,135 million VMT measured in 1998. This effect is certainly congruent with the results obtained in the present study (falling in the upper half of the range obtained from the 90% confidence interval on the effect of telecommuting). However, that informal calculation only accounts for travel savings due to telecommuting; it does not include any increases in travel due to factors such as non-work trip generation, residential relocation, and the realization of induced or latent demand. In contrast, the models estimated in the current study *do* account for such effects, because the observed VMT that constitutes the dependent variable in the model will include any such effects. The limited empirical evidence available on this question suggests that those travel-increasing effects are small relative to the savings, but whatever their magnitudes, they will act to reduce the transportation benefit of telecommuting. Thus, in our opinion, a reduction of 0.79% of VMT

[*] Specifically, (1) a 27-mile average round trip commute distance for telecommuters, (2) a factor of 0.76 for the proportion of commute miles that are drive-alone, and (3) an average telecommuting frequency of 1.2 days a week.

represents a reasonable upper bound on the effect of telecommuting on VMT in 1998, taking both internal statistical evidence and external reality checks into consideration.

On the other hand, it should again be pointed out that if the estimate of 15.7 million telecommuters is high, as some evidence suggests, then the impact on VMT will be accordingly lower. Another caveat is that when we are dealing with effects this small (perhaps only a fraction of a percent), the results are inevitably sensitive to model specifications. The estimated impact of telecommuting could be as high as 5% of VMT under at least one specification tested in the study (see Table 11 in the text), albeit one that we consider inferior to the final one selected. In general, the worse the first-stage model is (i.e. the less variation in VMT that is explained by variables other than telecommuting), the more powerful the effect of telecommuting will appear to be. Conversely, if we were able to improve the specification of the best first-stage model beyond the current adjusted R^2 of 0.65, there would be less residual variation for telecommuting to explain and its estimated effect could become weaker. In view of these issues and the endogeneity bias concerns, it would be dangerous to place too much emphasis on the specific quantitative results obtained here.

Airline PMT per capita: The preferred first-stage model has an adjusted R^2 of 0.55, and contains just two variables (plus the constant): GDP per capita, and gasoline price (lagged one year). In the second-stage model, telecommuting has a positive but insignificant coefficient. Thus, the safest (and plausible) conclusion is that telecommuting has no impact on airline travel, although the potential indication of a complementarity effect should be monitored in the future as additional data become available.

Total miles traveled per capita: Since ground VMT constitutes 79-91% of total miles traveled, the first-stage model for the latter variable closely resembles the one for the former variable, with a slightly higher adjusted R^2 of 0.67, and the same variables being significant. In the second-stage model, the telecommuting coefficient is also similar to its counterpart in the VMT model. As in that model, we can be 90%, but not 95%, confident that telecommuting reduced total miles traveled in 1998.

It is also of interest to comment on two variables that were *not* found to be significant in the final models: lane-miles and number of vehicles. The lane-miles variable is found to be significant in many induced demand studies that model VMT as a function of lane-miles as well as economic and other variables. Its absence here is presumably not due to correlations with included variables, since pairwise correlations and a factor analysis demonstrate that the lane-miles variable has very little variation in common with the other explanatory variables (in their first-differenced forms, as used in our models). However, if the time series in the induced demand studies were not made stationary before building the models, the significance of lane-miles could be due to third-party correlation with time (in raw form, lane-miles *is* highly correlated with the other variables in this study). Another difference with some of the induced demand studies is that we included lane-miles for all facility types, whereas some studies restricted their analysis only to higher-level facility types. By not including lower-level facilities such as minor arterials in the analysis, shifts in traffic from minor facilities to the major ones under study would erroneously be counted as induced demand.

Although conventional wisdom holds that vehicles themselves tend to induce vehicle travel, the number of vehicles variable was not found to be significant in our results. Similar to the lane-miles variable, the absence of this variable does not appear to be due to overly high correlations with included variables, but there could still be a subtle network of connections through correlations among number of vehicles per capita, employment, disposable income, and GDP. Based on the present results, it seems that if employment and disposable income are indirectly accounted for through the presence of GDP in the model, there is no residual effect of number of vehicles on VMT. However, here is a case where a more elaborate system of structural equations may be able to identify an effect that is not apparent in our single-equation model.

Recommendations

Given that telecommuting appears to have a statistically significant – albeit modest in magnitude – effect on reducing travel, several public policy recommendations suggest themselves.

First and perhaps foremost, better data is of paramount importance to a more precise determination of the true impact of telecommuting on VMT. As this study demonstrates, a great deal of uncertainty surrounds estimates of the number of telecommuters and frequency of telecommuting, and a wide range of answers to the question of "what impact on travel?" can be obtained. Telecommuting appears to be an important enough trend to justify the cost and effort required to collect reliable data with respect to its adoption and frequency, on an annual basis.

In view of its apparently beneficial transportation-related impacts, public agencies could consider several strategies for increasing the adoption of telecommuting. One such strategy is simply to collect and widely disseminate case-study information on telecommuting successes. Where costs and benefits can be quantified, the business case for telecommuting can be compelling. Case studies are more important in the many situations in which the costs of telecommuting may be evident and quantifiable, but the benefits may be less evident and less easy to quantify. Individual organizations are likely to be receptive to evidence showing that major competitors in the same industry have successfully adopted telecommuting and consider it a net benefit.

Public agencies have also occasionally considered (and some have implemented) tax credits for organizations who adopt telecommuting. However, the modest incentives that are usually involved in such proposals may not be sufficient in their own right to overcome the managerial resistance that often exists. Further, enforcement must be a concern, with possibly a high potential for false claims on the part of organizations or their employees. Even if reported telecommuting is genuine, to judge the cost-effectiveness of this policy it should be determined to what extent the reported telecommuting was in fact stimulated by the tax incentive, rather than something that would have occurred anyway.

Finally, one or more variables relating to the cost of transportation was significant in every model presented here, with a negative impact on travel. Thus, it stands to reason that policies that increase the cost of travel – congestion pricing, fuel taxes – will reduce the amount of travel, and by extension will make telecommuting more attractive. Although in this case more telecommuting is arguably just a desirable by-product of a policy oriented toward reducing travel directly (rather than a direct object of the policy itself), there may also be some additional transportation benefits accruing from the adoption of telecommuting itself. For example, some studies have found that telecommuting not only reduced commute travel, but non-work travel as well, and not only of telecommuters but also of their household members.

The encouraging transportation-related results obtained in this study, together with the other potential public and private benefits of telecommuting, certainly support further commitment to increasing its adoption, and further refinement of our knowledge of its impacts.

Table ES-1: Summary of Preferred Multivariate Time Series Models

Model	VMT per capita	Airline PMT per capita	Total miles traveled per capita
1st stage model			
No. of observations	33	32	33
Adjusted R^2	0.649	0.552	0.666
Constant	0.153 (4.866)	0.0655 (4.102)	0.132 (5.028)
GDP per capita	0.366 (3.936)	0.285 (2.449)	0.395 (5.093)
Gasoline price	-0.0936 (-3.847)		-0.0601 (-2.962)
Gasoline price (1st order lag)		-0.0827 (-3.882)	
Miles per gallon	0.352 (2.737)		0.257 (2.404)
CPI (all)	-2.076 (-3.990)		-1.516 (-3.496)
CPI (transportation)	0.834 (2.895)		0.539 (2.245)
2nd stage model			
No. of observations	11	11	11
Adjusted R^2	0.273	0.154	0.252
Constant	0.102 (2.284)	-0.0334 (-0.535)	0.109 (2.265)
The residuals of the corresponding model (1st order lag)		-0.608 (-1.940)	-0.479 (-1.547)
Natural log of the number of telecommuters (in millions)	-0.0499 (-2.183)	0.0169 (0.527)	-0.0535 (-2.254)

Notes:
All dependent and explanatory variables are the standardized, first-order differenced (i.e. $X_t - X_{t-1}$) variables.
The number in parentheses indicates the t-statistic for that coefficient. The degrees of freedom are N-k where k is the number of parameters estimated, and hence ranges from 8 to 29 for these models. Critical t-values for $\alpha = 0.05$ and 0.1, with 8 (29) degrees of freedom, are 2.306 (2.045) and 1.860 (1.699), respectively.

Table ES-2: Summary of Estimated Impact of Telecommuting on Miles Traveled in 1998 (using the 95% and 90% confidence intervals for the estimated coefficient of telecommuting)

Model		Change in annual distance per capita (miles)			% change in annual distance per capita			Change in annual distance per telecom-muter (miles)			Change in distance per occasion (miles)		
		Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
VMT per capita													
95%	50 occasions/year	-387	-190	7	-4.31	-2.12	0.08	-6,667	-3,274	119	-133.3	-65.5	2.4
	75 occasions/year										-88.9	-43.6	1.6
90%	50 occasions/year	-350	-190	-30	-3.89	-2.12	-0.34	-6,023	-3,274	-524	-120.5	-65.5	-10.5
	75 occasions/year										-80.3	-43.6	-7.0
Airplane PMT per capita													
95%	50 occasions/year	-94	28	150	-3.99	1.18	6.36	-1,617	479	2,575	-32.3	9.6	51.5
	75 occasions/year										-21.6	6.4	34.3
90%	50 occasions/year	-70	28	126	-2.99	1.18	5.36	-1,211	479	2,169	-24.2	9.6	43.4
	75 occasions/year										-16.1	6.4	28.9
Total Miles Traveled per capita													
95%	50 occasions/year	-589	-291	7	-5.19	-2.57	0.06	-10,138	-5,011	116	-202.8	-100.2	2.3
	75 occasions/year										-135.2	-66.8	1.5
90%	50 occasions/year	-531	-291	-51	-4.69	-2.57	-0.45	-9,145	-5,011	-877	-182.9	-100.2	-17.5
	75 occasions/year										-121.9	-66.8	-11.7

Notes:
A negative sign indicates a reduction in miles traveled, while a positive sign indicates an increase in miles traveled.
Based on 50 and 75 annual average telecommuting occasions, the change in miles traveled per occasion is calculated for each case.

1. INTRODUCTION AND MOTIVATION FOR THIS STUDY

Teleworking is defined for this report as working at home or a location closer to home than the regular workplace, using information and communication technology (ICT) to support productivity and communication with the supervisor, co-workers, clients, and so on. We here distinguish two main types of teleworkers: salaried employees of an organization, called telecommuters, and primary home-based business workers. In the former case we do not count after-hours work as telecommuting, if the employee still spends a full day at the regular workplace, and in the latter case we do not count second jobs that are home-based, if the primary job is not.

Telecommuters are assumed essentially to eliminate (or greatly reduce, if teleworking at a location other than home) the commute on days that they telecommute, although this is a simplification, since some research (Mokhtarian, 1998) suggests that about 6% of telecommuting occasions may still involve the normal commute (i.e. that telecommuting is only partial-day in those cases). For home-based business workers, on the other hand, the impact on transportation is not clear, since it is unknown what the alternative to the home-based business would be in each case. For many people the alternative is presumably a conventional job with a conventional commute, but for many others the alternative may be a part-time job or no job at all, in which case the commute "reduction" due to working at home is lower or non-existent. In fact, at least one study (Mokhtarian and Henderson, 1998) found that home-based business workers had a daily mean drive alone travel time one-third higher than home-based telecommuters (0.82 versus 0.62 hours), although not as high as conventional workers (1.14 hours).

In view of the ambiguity of the transportation impacts of home-based work, the difficulty in obtaining reliable data on its nature and extent, and the limited time frame of this study, we focus only on conventional telecommuting here. However, evidence indicates that home-based businesses enabled by ICT are a growing segment of the workforce (although their numbers currently appear to be smaller than those of salaried telecommuters). Thus, we believe that home-based business workers do merit analysis in future studies of this nature.

Telecommuting has been discussed as a strategy for reducing travel, and hence congestion, energy consumption, and air pollution emissions, since the term was coined by Jack Nilles in the 1970s (see, e.g., Nilles, *et al.*, 1976). In the US it has found its way into a number of public policy instruments, from regional transportation plans (SCAQMD and SCAG, 1989) and air quality regulations (SCAQMD, 1992) to state legislation (State of California, 1990; State of Florida, 1990; State of Washington, 1991; Gordon, 1992, 1993a, 1996; Castaneda, 1999) and Federal executive orders, laws, and programs (USDOT, 1990; Joice, 2000; Sec. 359 of H.R. 4475 (Wolf), Transportation Appropriations Act, signed into law October 23, 2000). Home-based businesses have not been the subject of the same attention, presumably because they already have the flexibility in choosing work times and locations that salaried employees are seeking to achieve through telecommuting. A current trend is to use the terms telecommuting and teleworking synonymously, with some policies referring to "teleworkers" but perhaps defining them more narrowly. Although we acknowledge the interest of some groups in focusing on the "work" aspect rather than the "commuting" aspect of the phenomenon, because of the heterogeneity of teleworking described above, we consider it useful to clarify whether the teleworker is a salaried employee or not, and hence will distinguish the terms teleworker(ing), telecommuter(ing), and home-based business worker as discussed above.

Telecommuting *per se* appears to have considerable popular appeal, offering employees the prospect of reduced commuting time, cost, and stress, more personal and/or family time, greater autonomy and ability to concentrate; and offering employers the potential of improved recruiting and retention, higher productivity, improved customer service (increased spatial and temporal reach), and savings on facilities costs. Several broad societal factors have combined to create a climate conducive to the adoption of telecommuting: "supply-side" factors include the increasing ubiquity, power, and ease of use of ICT, the globalization of the economy, and the need for corporate cost-cutting as well as for obtaining highly-skilled workers; and "demand-side" factors include sociodemographic trends such as two-career households and the aging population, time pressures and congestion, and stress (Handy and Mokhtarian, 1996b; Salomon and Salomon, 1984).

On the other hand, a number of barriers prevent telecommuting from achieving the penetration that might be expected from the list of driving and facilitating factors just described. On the employer side, conventional wisdom holds that management resistance to the concept ("how will I know they're really working?") is probably the largest single factor slowing adoption (see, e.g., Rognes, 1997, 1999). On the employee side, many workers whose jobs are well-suited to telecommuting and whose managers would permit it, do not choose to telecommute for a variety of reasons (preference for the interaction of the workplace, concerns about lack of visibility to management, lack of interest in organizing work to be done location-independently, a commute that fulfills some positive functions such as role transition, etc.; Mokhtarian and Salomon, 1994, 1996). At least one study (Varma, *et al*., 1998) has shown that a sizable proportion of people expressing serious interest in telecommuting never actually begin doing so, and half of those who do start have stopped (whether temporarily or not is unclear) within about a year.

Nevertheless, perhaps facilitated by several high-profile public-sector demonstration projects in the late 1980s and early 1990s (SCAG, 1988; JALA Associates, 1990; Kitamura *et al.*, 1990; Quaid and Lagerberg, 1992; Ulberg, *et al.*, 1993), the adoption of telecommuting has apparently been steadily increasing over the past two decades, even if not as rapidly as its enthusiasts may have predicted. The data available suggests that about 12% of the workforce telecommuted at least once a month in 1998 (see Section 4.3 for a discussion of the quality of these data), with an average annual growth rate of 23% since 1988.

Telecommuting can potentially offer a number of societal benefits. In addition to the congestion-reduction and related advantages already mentioned, some prospective benefits claimed for telecommuting (e.g., Barr, 2001; Normann, 2000; Pratt, 1991; Sato and Spinks, 1998; USDOT, 1993; USDOE, 1994) include the employment of broader segments of the workforce and related economic development, strengthening families and local communities, reducing residential-area crime (through greater neighborhood monitoring by home-based workers), improving public health (through reduced exposure to traffic accidents and communicable diseases, as well as reduced stress), and offering a response to foreseen (e.g. the Olympics) or unforeseen major events affecting workplaces (e.g. the September 11, 2001 terrorist attacks on the World Trade

Center and Pentagon, or a major fire or flood) or the transportation system (weather emergencies, earthquakes, major construction projects).

All of these benefits are largely speculative; while anecdotal evidence for each of them is available, to our knowledge there has been virtually no rigorous empirical study of their extent at an aggregate level. This is true even for the putative transportation benefits, which have been the major (although not the exclusive) focus of public policy with respect to telecommuting. A number of small-scale empirical studies (Hamer *et al.*, 1991, 1992; Henderson *et al.,* 1996; Henderson and Mokhtarian, 1996; Koenig *et al.*, 1996; Mokhtarian, 1991, 1997, 1998; Mokhtarian and Varma, 1998, Mokhtarian *et al.*, 1995; Nilles, 1988; Pendyala *et al.*, 1991; RTA, 1995) have established the short-term transportation (and air quality) benefits of telecommuting at the disaggregate level: vehicle-miles traveled are substantially reduced for those who telecommute, on days that they telecommute, for as long as they telecommute. The question is whether that impact "scales up" to a systemwide level. It has been suggested (Mokhtarian, 1998) that it will not, in view of the relatively small amounts of telecommuting occurring today, the relatively slow growth that can be expected as the phenomenon matures and as attrition continues to occur, and the likelihood of long-term indirect impacts partly counteracting the short-term direct savings. Nevertheless, to our knowledge an aggregate study of the impact of teleworking on transportation has not previously been conducted, and that is the purpose of the present study.

In general, the impact of telecommunications on travel can take several forms (Salomon, 1986; Mokhtarian and Salomon, forthcoming). Substitution of telecommunications for travel is the impact most desired from a public policy perspective, but it is not the only possibility. In particular, telecommunications may also have a complementary relationship to travel (Mokhtarian, forthcoming), through increasing the size of one's contact set (which forms the basis for generating travel for face-to-face interaction), through facilitating or generating travel directly (e.g. the use of ICT to support organizing in-person meetings, or last-minute auctions of airline seats through the Internet), through supply-side applications such as Intelligent Transportation Systems technology increasing the effective capacity of the transportation system, or through freeing time from other activities (including but not limited to traveling), some of which time may then be devoted to more traveling.

It should be kept in mind that transportation can have similar substitution and complementary effects on telecommunications as well. To fully assess the interactive relationships between these two indicators, measures of complete amounts of both transportation and telecommunications, and models allowing both directions of causality, are needed. Studies focusing only on a small subset of telecommunications activity (e.g., telecommuting) and investigating only a single direction of causality (telecommuting affecting travel) are necessarily incomplete. In fact, it has been argued (Mokhtarian and Meenakshisundaram, 1999) that such narrowly-focused (and generally short-term) studies of direct (and unidirectional) impacts are more likely to identify a substitution effect, whereas complementarity effects are more indirect and potentially longer-term, and hence less likely to emerge in such contexts.

Thus, a complete study of the aggregate relationships between telecommunications and travel would ideally involve a structural equations model system allowing each measure to affect the other over time. A few aggregate studies have taken related approaches. Plaut (1997) performed an input-output analysis of industrial consumption of transportation and communication services by nine countries of the European Community in 1980. She found strong evidence of complementarity, in the sense that use of transportation was strongly correlated with use of communications. However, the results do not speak to the degree of direct causality between the two sectors: the observed correlations may be due in some part to independent mechanisms that separately generate congruent transportation and communication demands.

Another aggregate study focused on per capita consumption expenditures on private transportation, public transportation, and communications. Using 1960-1986 time-series data from Australia and the United Kingdom, Selvanathan and Selvanathan (1994) estimated a simultaneous equation system of the consumer demand (in monetary terms) for these three kinds of goods separately, plus all others combined. Interestingly, this study found a pairwise substitution relationship among all three sectors.

In reconciling these two studies, Mokhtarian and Salomon (forthcoming) suggest that the effects of complementarity may apply more cogently at this point to industry than to consumers, but that this may be changing (and may have already changed considerably from the 1986 endpoint of the data analyzed in the Selvanathan and Selvanathan study); the different methodologies used in the two studies is also a confounding factor. In any case, Plaut (1997) points out that industrial expenditures on transportation and communications account for half to two-thirds of the total in Western countries, and hence the findings for industry are likely to dominate the overall relationships among these sectors of the economy. To our knowledge, however, no studies have explored the aggregate relationships between physical (as opposed to economic) measures of passenger travel and telecommunications, assessing the extent of causality by accounting for other variables that can be expected to influence both.

Such a bi-directional structural equations model with aggregate time series data is beyond the scope of the current project. In the present study, we focus on a single direction of causality and a subset of all telecommunications activity, to explore the impact of telecommuting on vehicle-miles traveled (VMT). This is a limitation that must be kept in mind in interpreting the results. In fact, as indicated by the discussion in Section 2, VMT should properly be modeled in a system of multiple structural equations. For example, VMT is influenced by the fleet size (number of registered personal vehicles), which in turn is a function of the number of licensed drivers, levels of employment, and number of households, which in turn are functions of the population size. In addition, VMT is influenced by transportation supply indicators such as number of lane-miles, but also influences supply through pressures to relieve rising congestion caused by rising demand. Congestion directly, and VMT indirectly, influences the level of telecommuting, in a direction that counteracts the hypothesized influence of telecommuting on VMT: more travel should stimulate more telecommuting, but more telecommuting reduces travel. Telecommuting is also influenced by the same transportation supply and price variables postulated to influence VMT directly. And, like VMT, levels of telecommuting are also functions of population and employment as well as other variables.

Thus, the single-equation results presented here are inevitably subject to the endogeneity bias that occurs when explanatory variables in a single equation are actually endogenous to the system of interest rather than exogenous influences on the dependent variable of the equation. With that caveat in mind, however, the tentative results that can be obtained here are still of interest for the new insight they may be able to provide into the relationship between telecommuting and travel at the aggregate level – in particular to see whether the substitution effect observed in the disaggregate studies can be replicated. It is possible that, after filtering out other forces expected to influence aggregate VMT, telecommuting may have an effect that can be detected. It can also be pointed out that the same endogeneity bias affects most other aggregate models of VMT in the literature, including the studies mentioned in Section 2.

In the next section, we describe the dependent variables of this study more specifically, and discuss some of those "other forces" (explanatory variables) that are hypothesized to influence VMT. In Section 3 we provide a brief overview of the Box-Jenkins time series modeling approach employed in this study. Section 4 introduces the data used to perform the analysis, including sources and key limitations, and offers some basic descriptive information on each variable. In Section 5 we present the modeling results: first, univariate models for each key variable (dependent and explanatory), then models containing all explanatory variables except telecommuting, and finally models containing telecommuting to see if it adds significant explanatory power. Section 6 contains some conclusions and recommendations.

2. HYPOTHESIZED RELATIONSHIPS

The product of a transportation system is the *amount of travel* it facilitates. That amount includes the movement of goods, but in the current study we treat only passenger travel. Generally, people travel for the purpose of engaging in activities (work, education, maintenance and leisure) which provide a positive utility to the individual and contribute to her or his welfare. The amount of passenger travel in a system is commonly expressed in terms of *person-miles traveled* or PMT. The magnitude of PMT can be measured through the use of travel surveys in which sampled individuals are requested to report on all trips made in a given period. Such surveys generally now include travel by non-motorized modes such as walking or biking, as well as by public transit and other modes.

When addressing the negative externalities of transportation systems (such as pollution and congestion) the relevant product of a system is measured not in the number of people moved but in terms of *vehicle-miles traveled* or VMT. VMT will always be smaller than the corresponding PMT, but the amount by which this is true will depend on the extent of travel by modes other than the personal vehicle, and on the occupancy level of personal vehicles.

It is the movement of vehicles, and not of people, which generates air pollution, noise and congestion. Thus, VMT is the primary dependent variable of the current study. This choice is in keeping with the motivation of understanding the potential energy savings that can be attributed to telecommuting, as one policy tool among many other travel demand management techniques.

In actuality, we focus on two dependent variables in this study. The first, as just indicated, is annual passenger vehicle-miles traveled, i.e. miles traveled by light-duty autos and light-duty trucks in the US in a given year. We will sometimes refer to this variable as "ground VMT", or simply VMT. The second dependent variable is the sum of ground VMT and airline passenger-miles (PMT), referred to as "total miles traveled" (this is a simplification, of course). For completeness, we also model airline PMT separately. The purpose of analyzing total miles traveled is to provide some of the broader perspective mentioned in Section 1. It may be the case that telecommunications technology is influencing slower growth in ground VMT. But at the same time, increasing economic prosperity may be influencing faster growth in travel, in particular motivating the increasing substitution of faster modes such as airplane for slower modes such as auto (Schafer, 1998). Further, as mentioned earlier, complementarity effects between transportation and telecommunications are more likely to be detected at a broader scale than a narrower one. Thus, the effect of telecommuting on travel may be very different for ground VMT only than it is for total miles traveled[1].

Trends in both ground VMT and airline passenger miles have been studied extensively. Especially, many researchers and policymakers have been interested in gasoline demand, VMT and fuel efficiency since the oil embargo in 1973 (Dahl, 1986). Many studies in the literature (e.g., Springer and Resek, 1981; Gately, 1990; Greene, 1992; Jones, 1993; Schimek, 1996) have modeled VMT as a function of income (GNP or GDP), gasoline price and fuel efficiency using aggregate time series data. Here, we focus on ground VMT and examine some key trends expected to affect it. Many of the types of variables expected to affect VMT can also be expected to affect airline travel.

In a study of the 1990 Nationwide Personal Transportation Survey (NPTS), Pisarski (1992) identified a number of factors that potentially affect VMT (also see Nelson and Niles, 2000 for a discussion of factors affecting non-work VMT in particular). The factors conventionally hypothesized to be important can be broadly divided into two groups: those that increase (or decrease) the miles traveled by an individual vehicle, and those that result from a change in the size of the vehicle fleet. It is clearly possible that individual cars will reduce or maintain a given level of usage but that VMT will increase as a result of a growing population. On the other hand, the evidence shows that VMT is growing faster than the population, indicating that per capita VMT is increasing for a variety of reasons. The following subsections will first present the vehicle-level effects and then the population-based effects. The discussion in this section is at a conceptual level; in Section 4 we address operationalizing the relationships described here with available data.

2.1 Growth in VMT per Vehicle

People travel in order to participate in desired activities. The ***activity level*** is strongly affected by the state of the economy. When economic conditions improve, people are likely to engage in more, and more specialized, activities, thus generating more VMT than that produced during economic recessions. At the disaggregate level, income is well-known to have a significant influence on the amount of travel demanded, and at the aggregate level, travel demand rises with any of various indicators of economic prosperity.

Suburbanization, which has accounted for much of the urban growth over the last half century, was facilitated by the private car and the widespread preference for lower-density, single-family

[1] Note that even the ground VMT variable used in this study – annual nationwide VMT – includes work as well as non-work travel, long vacation trips by car as well as daily travel, and travel by urban dwellers as well as rural farmers. The data do not permit separating out only daily short-distance travel, for example – the segment of VMT most likely to be directly affected by telecommuting.

housing. Lower densities mean greater spatial separation between origins and destinations, and in turn reinforce the dominance of the automobile by making transit and walking or biking less practical or attractive. Hence, suburban living has contributed to the growth in vehicle travel, not only for commute trips but also for other activities. However, since the suburbanization of the residential sector has been (and is still being) followed by the suburbanization of services and employment, the growth of VMT due to this process is probably slower than three or four decades ago.

The ***cost of traveling*** is expected to be an important factor in explaining the growth or decline in the production of VMT. Its effect may occur in several different ways. First, increases in fixed costs, specifically the fixed costs of owning an automobile, may discourage auto ownership and hence affect VMT through the fleet size category of factors discussed below. Second, increases in both fixed and variable costs (such as fuel prices, parking, and possibly road pricing) may have an effect on mode choice. Higher costs may, in principle, encourage ridesharing and the use of public transportation, thus increasing vehicle occupancy and reducing VMT. Finally, increases primarily in variable costs are expected to reduce trip rates and trip lengths. Telecommuting is in fact a special case of this effect, although travel costs are by no means the only, or even necessarily the most important, reason people give for telecommuting (Mokhtarian, *et al.*, 1998). The magnitude of such an effect depends on the elasticities (with respect to price) of the demand for travel for various purposes.

The trend is toward a reduction in private transportation costs, despite common claims to the contrary. During the period covered by this study, the Consumer Price Index (CPI) for private transportation is generally lower than the overall CPI, while the CPI for public transportation is generally higher. Thus, at least this indicator of travel costs will likely contribute to increases in VMT. Certainly, there is a long-term trend in the US of declining patronage of public transportation and diversion of travel to private vehicles, both in share as well as in absolute terms. There is further a trend toward declining vehicle occupancies (Hu and Young, 1999), pushing VMT closer to PMT. Another (modest, but interesting) contribution to VMT comes from the modal switch away from walking or bicycle use by children, due to the growing phenomenon of parents driving children to school and other activities. This seems to be the combined effect of a rise in the standard of living and a decline in perceived community safety.

A special case of transportation costs that may deserve a category of its own is the ***supply of transportation***. Increasing the supply of transportation decreases travel costs through reducing the time required to access a given set of opportunities, as well as increasing the accessibility to more opportunities. An extensive literature debates whether the addition of new roadway capacity will induce new travel demand. A number of studies (Hansen and Huang, 1997; Fulton, *et al.*, 2000; Noland and Cowart, 2000; Noland, 2001) have addressed this issue by modeling VMT (at various levels of aggregation) as a function of roadway lane-miles as well as economic indicators, and finding a significant effect.

2.2 Size Effects Contributing to the Growth of VMT

Population growth contributes to the growth of VMT. Assuming that vehicle ownership levels do not change dramatically, the addition of new people of any age (whether through birth or immigration) and new ***licensed drivers*** will increase the demand for travel and for personal vehicles, respectively. Of course, there will be variations in travel demand and vehicle ownership by income, residential location (central cities vs. suburban and exurban), age, and other variables, but at the aggregate level the relationships of these size variables to VMT can be expected to be quite strong and relatively stable.

Households constitute the basic unit of consumption. All else equal, 100 people are likely to own more vehicles if those people are spread among 75 households than if they are spread among 50. Thus, separately from increases in population, declining household sizes and hence a disproportionate increase in the ***number of households*** will also increase the fleet size. ***Employment*** levels will also affect the demand for personal vehicles, both as a virtual necessity for access to employment opportunities for most people[2], and also because of the increase in income that employment brings.

Finally, ***fleet size*** itself will definitely contribute to VMT, as vehicles are obtained for the purpose of using them. The relationship is not purely proportional, however, since the marginal impact of each vehicle on VMT typically diminishes as the household acquires more vehicles. An additional factor is the fleet age. Generally, older cars travel less than new ones, possibly reflecting an income effect.

3. BOX-JENKINS TIME SERIES MODELING APPROACH

A "time series" is a set of observations on a given variable (such as VMT) taken at a number of (usually equally-spaced) points in time. The object of time series analysis is to model or explain the past behavior of a particular series, and therefore to be able to predict the future behavior of that series as well. In the current context, the purpose is to examine whether telecommuting has had a detectable impact on VMT over time. In this section, we briefly explain some basic concepts of time-series analysis, taking the widely-practiced Box-Jenkins (1976) approach.

3.1 Some Basic Univariate Time Series Analysis Concepts

Suppose we are interested in explaining the behavior of the time series $\{Y_t\}$. In general, Y_t cannot be described as an exact deterministic function of time such as $Y_t = a\ t$ or $Y_t = t^b$. The simplest model is that Y_t is a random or stochastic process over time. However, the fact that Y_t is stochastic does not mean that it is totally unpredictable; the plot of a time series will typically indicate patterns in the data that repeat over time. Thus, we can express Y_t as the sum of a systematic component N_t, and an unsystematic, or "random shock" component a_t: $Y_t = N_t + a_t$.

The object of *univariate time series analysis* (that is, modeling Y_t without reference to any other variables) is to discover the nature of the systematic component N_t. This component is expressed in terms of past values of Y and/or a. There are two basic univariate models. The first model, called *autoregressive (AR) of order p*, is

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[2] There is probably a bi-directional causality effect here: certainly prior ownership of a vehicle affects one's ability to find, interview for, and accept a job, but in many cases obtaining a particular job may afterwards necessitate acquiring a car to make the commute practical.

$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + a_t$.

That is, Y_t is a direct combination of the last p values of the series, plus a random shock a_t. The second model, called *moving average (MA) of order q*, is

$Y_t = a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-q}$

(where the minus signs are an arbitrary convention). That is, the influence of the random shocks themselves (representing relevant but unmeasured variables) persists, so that Y_t is a function of the last q shocks, plus a new one. It is possible to have a mixed autoregressive-moving average process, but it is virtually unknown in practice.

The first step in analyzing a series such as $\{Y_t\}$ is to make sure it is *stationary* (i.e., does not increase or decrease over time, on average), since key results with respect to the validity of the estimated parameters are based on an assumption of stationarity. In a multivariate time series context, it can be intuitively understood that when two series are both increasing over time, they will show a strong *apparent* relationship to each other simply because each is strongly correlated with time, whether or not there is a genuine relationship between them (Greene, 1997). It is important to control for that "third-party" correlation before analyzing the true relationship between two series.

A non-stationary series may not exhibit an obvious trend (especially if there are deep fluctuations), and conversely, in a series that seems to display a trend, the actual magnitude of the trend may be insignificant relative to the base series. Thus, while visual examination of a plot of the series is helpful, more systematic approaches are available and preferable for identifying (non-) stationarity. Non-stationary series can normally be made stationary by differencing them (i.e. by modeling $Y_t - Y_{t-1}$ instead of Y_t), or by applying a transformation such as taking the log or square root, or squaring the variable.

3.2 Multivariate Time Series Analysis

While modeling Y_t in terms of its past history alone often provides a lot of information (and may be worth doing when no more sophisticated analyses are possible), it is usually an incomplete approach, both conceptually and practically. Univariate time series analysis has been called "modeling ignorance", because relating Y_t to the past has no causal implications. That is, Y_t is normally not actually *caused* by past values of Y, it is merely *similar* to them. Y_t is caused by other variables X_t, and the similarity of Y_t to its past is due to similar causes operating in the past. If a causal variable X_t suddenly ceased to be similar to its past (e.g. due to a policy change or a natural intervention), knowing only previous values of Y would be of little value in predicting future ones, whereas knowing the relationship of Y to X would be of great value. Accordingly, we employ *multivariate time series analysis*, for which

$Y_t = f(X_t) + N_t + a_t$.

It is customary to engage in a step-by-step model-building process, in which (1) as much variance in Y_t as possible is accounted for using only the past history of Y (i.e. by modeling N_t), and (2) as much more of the variance as possible is explained using causal variables X_t. In our context, the second step will be disaggregated further into two stages. Since we are trying to assess the potential effect of telecommuting on VMT, the conservative, scientifically rigorous approach is to model the effect of other, more conventional variables on VMT first, and then see if any of the *remaining* variation in VMT_t can be explained by telecommuting.

Although model-building, diagnosis, and model revision takes place step by step, customarily all parameters from earlier steps are re-estimated simultaneously with parameters relating to the current step. This makes the most efficient use of the data, and allows all parameters to be estimated as precisely (with the greatest confidence) as possible. In the present context, however, we deviate from that practice slightly, because of the fact that the time series for telecommuting is so much shorter (11 annual observations, 1988-1998) than those for the other variables (34 years, 1966-1999). Estimating the final model, containing telecommuting, "from scratch" would mean the loss of many data points and hence degrees of freedom, making the resulting model statistically unreliable. Instead, we conduct all but the last stage of modeling on the full data set containing 34 years of observations. Next, we compute the unexplained residual of VMT from that model. Finally, using only the 11 observations corresponding to the years 1988-1998, we model that residual time series as a function of telecommuting.

3.3 The Box-Jenkins Methodology for Time Series Analysis

The object of the Box-Jenkins approach is to obtain the most parsimonious model that is still an adequate representation of the data. The approach consists of three steps: identification, estimation, and diagnosis. *Identification* involves formulation of a tentative hypothesis about the nature of the model (e.g., about the exact form of N_t). The identification is suggested by patterns either in the raw series itself, or in the residuals from a previously-estimated model. Simultaneous *estimation* of the parameters of the identified model is done with one of a number of special-purpose routines devoted to time-series analysis. Finally, the residuals from the estimated model are *diagnosed* to see if there are any patterns left that indicate an incorrect or incomplete specification.

If the model is well-specified, the residuals a_t should form a series with no apparent pattern. Such a totally random series is called "white noise". If the residuals do not form a white noise series, the patterns that are there may suggest an improved identification of the model. The new model is then estimated and the residuals diagnosed. Note that the achievement of white noise generally signifies the completion of that stage of model-building, but not necessarily of the entire process. The addition of more variables to the model can explain some of the white noise, reducing its variability or amplitude and thus the influence of unknown variables on Y_t. This is obviously desirable, and so the aim is not only to achieve white noise in the residuals, but the lowest possible level of white noise.

To summarize, the steps that we will be taking in this analysis are as follows:

1. Conduct univariate analyses both on VMT_t and on each explanatory variable X_t, including first ensuring stationarity for each series (through differencing or transformations as needed),

and then explaining as much variance as possible through univariate AR or MA models, until white noise is achieved for the residuals of each series.

2. Model the stationary VMT_t as a function of its own past history and all the explanatory variables except telecommuting, refining the specification until white noise is achieved for the residuals.

3. Model the 1988-1998 residuals of the VMT_t series as a function of the amount of telecommuting occurring.

4. DESCRIPTION OF THE DATA USED IN THIS STUDY

4.1 General Comments

Section 2 discussed a number of hypothesized influences on VMT. Efforts were made to obtain data on the key types of influences described there: economic factors, transportation price and supply factors, and demographic factors, in addition to telecommuting. The variables used in this study include those appearing most often in models of VMT identified in our review of the literature. It was also necessary, of course, to obtain data on the dependent variables, VMT and airline passenger-miles. Due to the lack of availability of reliable data on the amount of telecommuting at any lower level of aggregation, all variables in this study are measured at the nationwide level.

Of necessity due to time and resource constraints, this study relies on secondary sources for the data analyzed. It is helpful to clarify some basic issues associated with the use of secondary data in research of this type. Secondary data are items of information collected by individuals or agencies other than the researchers performing the study in question. Secondary data may not represent the exact variables desired by the researcher. Moreover, the definitions of variables may change over time and such changes may not be reported, or reported to the desired level of detail. The quality control exercised by other data collection agents with regard to issues such as sampling, analysis of non-response, and missing data is often not clearly-specified, and may not conform to the standards or decisions desired by the researcher. Of course, it should be noted that even if collecting primary data, the researcher may also not be able to obtain the ideal data.

The next subsection briefly discusses the definitions, sources, and key issues associated with each variable used in this study, except for telecommuting, which is separately addressed in the following subsection. Section 4.4 illustrates the raw data with plots, and presents pairwise correlations between the variables. In Section 4.5 we describe the factor analysis of the explanatory variables other than telecommuting, conducted to consolidate the numerous highly correlated variables into a smaller set of composite variables representing quasi-independent underlying dimensions in the data.

4.2 Variables Included in this Study

Below, we provide brief definitions of each variable, plus a discussion of important measurement issues. Table 1 documents the sources from which data on each variable was obtained. All data on vehicle miles traveled (VMT), number of vehicles, and fuel efficiency and consumption

Table 1: Summary of Data Sources for Variables

Variable	Source
Ground VMT (absolute, and per capita)	FHWA, *Highway Statistics*, each year. < http://www.fhwa.dot.gov/ohim/ohimstat.htm >
Airline revenue passenger-miles (absolute, and per capita)	Civil Aeronautics Board (CAB), *Air Carrier Traffic Statistics*, each year. Bureau of Transportation Statistics, *Air Traffic Statistics and Airline Financial Statistics,* 2001. < http://www.bts.gov/oai/indicators/top.html > Bureau of Transportation Statistics, *National Transportation Statistics*, each year. < http://www.bts.gov/btsprod/nts/>
GDP per capita	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Disposable income per capita	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Employment per capita	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Unemployment rate	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Federal Interest Rate	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Gasoline price ($ per gallon)	Energy Information Administration, *Annual Energy Review*, 1999. < http://www.eia.doe.gov/emeu/aer/contents.html >
Fuel efficiency (miles per gallon)	FHWA, *Highway Statistics*, each year. < http://www.fhwa.dot.gov/ohim/ohimstat.htm > Energy Information Administration, *Annual Energy Review*, 1999. < http://www.eia.doe.gov/emeu/aer/contents.html >
Consumer Price Index (all)	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
CPI (transportation)	U.S. Government Printing Office, *Economic Report of the President*, 2001. < http://w3.access.gpo.gov/eop/ >
Population	Population Estimates Program, Population Division, U.S. Census Bureau, < http://www.census.gov/population/estimates/nation/popclockest.txt >
Average household size	Population Estimates Program, Population Division, U.S. Census Bureau, < http://www.census.gov/population/socdemo/hh-fam/tabHH-6.txt >
Licensed drivers per capita	FHWA, *Highway Statistics*, each year. < http://www.fhwa.dot.gov/ohim/ohimstat.htm >
Number of personal vehicles per capita	FHWA, *Highway Statistics*, each year. < http://www.fhwa.dot.gov/ohim/ohimstat.htm >
% suburban population	U.S. Census Bureau, *Revised Standards for Defining Metropolitan Areas in the 1990s*, 2000. < http://www.census.gov/population/www/estimates/mastand.html > U.S. Census Bureau, *Statistical Abstract of the United States*, 2000. < http://www.census.gov/statab/www/ > U.S. Census Bureau, *The New Metropolitan Area Definitions*, 1990 Census of Population and Housing Supplementary Reports, 1993.

(Table 1 continued)

Variable	Source
% suburban population	U.S. Census Bureau, *Standard Metropolitan Statistical Areas and Standard Consolidated Statistical Areas: 1980*, 1980 Census of Population Supplementary Reports, 1981. U.S. Census Bureau, *Population Annexed to Central Cities of Standard Metropolitan Statistical Areas in the United States between 1960 and 1970*, 1970 Census of Population Supplementary Reports, 1972. U.S. Census Bureau, *Population of Standard Metropolitan Statistical Areas: 1960 and 1950*, 1960 Census of Population Supplementary Reports, 1961.
Lane-miles	FHWA, *Highway Statistics*, each year. < http://www.fhwa.dot.gov/ohim/ohimstat.htm >

include the 50 US states and the District of Columbia. These data are classified by vehicle type (car, truck, and all motor vehicles), and calculated by the Federal Highway Administration (FHWA). The car category is the only one used in this study; it includes passenger cars, motorcycles, and other 2-axle 4-tire vehicles such as vans, pickup trucks, and sport utility vehicles.

Before 1966, the "other 2-axle 4-tire vehicle" category was combined with trucks. To maintain consistency in the measurement of personal-vehicle-miles traveled, the key variable of this study, we elected to begin the analysis with 1966. Reinforcing this decision was the fact that some other variables (notably number of licensed drivers and data on several economic indicators such as the Consumer Price Index, disposable income, and the Federal interest rate) also had some key changes in measurement or availability in years close to (although earlier than) 1966. Thus, most time series analyzed here have 34 observations, from 1966 to 1999.

Although this is a long enough series to be meaningful, more is nearly always better in statistical analysis, and the relatively small number of observations did influence various modeling decisions. Our general approach was to conserve degrees of freedom by specifying models as parsimoniously as the empirical evidence permitted. To take an extreme example, if we first-differenced the variables to achieve stationarity (thereby "losing" the first observation in each series), and then included all 15 explanatory variables in the model, both contemporaneously and lagged by one period to allow for delayed effects (thereby losing the second observation in each series), we would be estimating 31 parameters (30 coefficients of the contemporaneous and lagged explanatory variables, plus the constant term) using 32 cases. Obviously the resulting model (while having an extremely high goodness-of-fit) would not be very generalizable. Thus, in a data set this small, each degree of freedom counts.

Annual VMT

The measurement of aggregate VMT is difficult. One method, used in the Netherlands, is based on panel data in which vehicle owners periodically report their odometer readings. This method can produce a reliable estimate of VMT provided that the sample is representative of the vehicle population. In the US, however, VMT is calculated by the states' Departments of Transportation, generally on the basis of traffic counts per network link.

Specifically, total VMT is annually reported by each state to the Federal Highway Administration. It is calculated by multiplying daily VMT times 365 days (366 days for leap years). Daily VMT is generally based on a product of the annual average daily traffic (AADT) on a given highway link and the centerline length of the corresponding link. AADT is generally obtained through counts of traffic on a given link over a 24- or 48-hour period, at one or more times of the year, with the results seasonally adjusted. All segments of interstate highways and other principal arterials are required to have new counts made at least once every three years (i.e. with at least a third of such segments sampled each year). In between new counts, AADT for a given segment is updated by applying estimated growth factors. AADT for the lower functional classifications (minor arterials and below) is generally based on counts taken on sampled segments. Some states estimate VMT for those functional classifications using fuel tax revenues (indicating how many gallons of fuel are sold) and data on fuel efficiency (miles per gallon) of the fleet.

It can be seen from this description that VMT estimates can have many sources of error: sampling (both of links and of days; Kumapley and Fricker, 1996), measurement (fallible counting devices, difficulty in determining what proportion of a mechanically-obtained count represents two-axle versus three-or-more-axle vehicles, inconsistent definitions between states), extrapolation to non-counted years, and so on. Nevertheless, at the nationwide level, measurement of the *growth* of VMT over time can be reasonably reliable, if the errors tend to have a consistent effect from one year to the next and hence cancel out when comparing differences between years.

We explored models expressing VMT both in absolute terms and on a per capita basis. Several models of each form of VMT are presented in Section 5.2.1.

Airplane Passenger Miles

This variable indicates total revenue passenger miles traveled on domestic airlines. Air carrier employees and infants are not counted as revenue passengers. Included are scheduled or nonscheduled, domestic or international flights by certificated domestic air carriers operating in the US. Certificated air carriers are classified into four groups based on annual operating revenues: majors, nationals, large regionals, and medium regionals. In 1979, deregulation prompted the entry of many small carriers into commercial aviation, resulting in the rapid increase in passenger miles seen for that year.

Real Gross Domestic Product

Gross domestic product (GDP) is the market value of the goods and services produced by labor and property located in the US. It is based on chained (1996) dollars (calculated by using the gross domestic product implicit price deflator, and called "real") to provide a valid comparison over time. To reduce collinearity with population, this variable is included in the model in per capita form (dividing GDP by the population size).

Disposable Personal Income

This variable measures personal income less personal tax and nontax payments. It is based on chained (1996) dollars. We use the per capita form.

Employment and Unemployment

The civilian labor force comprises employed and unemployed persons. The employment variable indicates the number of employed persons 16 years or older. It appears in the model in per capita form. The unemployment rate is calculated as the ratio of unemployed individuals to the total civilian labor force.

Federal Funds Interest Rate

This variable measures the average interest rate of federal funds. As an indicator of the demand for money (e.g. for investment), a high FIR generally corresponds to a strong economy.

Real Motor Gasoline Price

This variable measures the average motor gasoline price in dollars per gallon. It is calculated from a sample of service stations (including full-, mini-, and self-serve), in 55 (1966-1973), 56 (1974-1977), and 85 (1978 and beyond) urban areas, respectively. It is based on chained (1996) dollars.

Fuel Efficiency (Miles per Gallon)

This variable measures average vehicle-miles traveled per gallon, dividing total VMT by total fuel consumption. Fuel consumption, in turn, is derived from state fuel tax records, considering the impact of continuously improving tax compliance and changes in Federal and state fuel tax laws. FHWA estimates fuel consumption by vehicle type based on miles per gallon for both diesel- and gasoline-powered vehicles using the 1992 Truck Inventory and Use Survey and other sources.

Consumer Price Index (CPI)

The Consumer Price Index (CPI) is calculated by the Bureau of Labor Statistics to measure "the average change in price over time in a fixed market basket of goods and services bought by consumers for day-to-day living" (www.bls.gov/wh/cpibrief.htm, accessed July 3, 2001). This variable is based on 1982-84 = 100 for all urban consumers. We consider both the CPI for all items, and the CPI for transportation items only (including private and public transportation).

Population

This variable is estimated by the Bureau of Census based on the decennial census data.

Household Size

The Census Bureau publishes annual data on the number of households in the US, based on the decennial census and the Current Population Survey. To reduce collinearity with the population variable, we focused on using average household size, but also explored models incorporating number of households directly.

Number of Licensed Drivers

This variable measures the total number of licensed drivers. To reduce collinearity with population, we use it in per capita form.

Number of Registered Vehicles

This variable measures the number of personal vehicles registered; we use the per capita form (but also experimented with it in its original form).

Percent Suburban Population

Metropolitan areas are subdivided into two categories: "inside central city" and "outside central city", or suburban. The proportion of the metropolitan population living in suburban areas was used as a measure of suburbanization, which is hypothesized to increase VMT due to lower densities requiring more and longer vehicle trips. During the span of time covered by this study, data on the sizes of the central city and suburban populations were directly available only for the four decennial census years 1960, '70, '80, and '90. We used those four observations to fit two models (of central city and suburban population, respectively), using metropolitan area population and a constant term as the only explanatory variables (adjusted R^2s = 0.949 and 0.999, respectively). Those equations were then used to predict central city and suburban populations in non-decennial years, and the resulting series of suburban populations was divided by the sum of the two populations in each year to obtain the proportion of the metropolitan population living in suburban areas. The difference between the observed values in decennial census years and predicted values in the interim years results in minor discontinuities appearing at decade years, as seen in the plot shown in Section 4.4 (Figure 1).

Lane Miles

Since 1984, this variable has been estimated by FHWA, separately for 12 categories: interstate, other principal arterial, minor arterial, major collector, minor collector, and local – each of those for rural and urban areas, respectively. For a given roadway segment, lane miles are obtained by multiplying the centerline length by the number of through lanes in that segment (where, for the rural minor collector and the rural/urban local functional systems, the number of through lanes is assumed to be two). The definition of the number of through lanes is "the prevailing number of lanes in both directions carrying through traffic in the off-peak period. It excludes lanes used for parking, turning, collector-distributor operations, weaving, service ramps, bus pullouts, climbing lanes and vehicle run away ramps, etc." (www.fhwa.dot.gov/ohim/hs99/hpms.htm, accessed July 7, 2001, *Highway Statistics 1999*, Section 5, p. 6).

Between 1980 and 1983, "road length" (total centerline miles) in each of the same 12 categories was available, but not lane miles. Prior to 1980, not only were lane miles not available, but road length was only available in the form of rural and urban totals. Thus, we estimated total lane miles between 1966 and 1983 in two steps. First, we used the complete data available from 1984 to 1999 to calibrate linear regression models predicting lane miles in each category as a function of road length[3]. We then used those models to backcast lane miles in each category between 1980 and 1983, and summed across categories to obtain total lane miles for those years.

In the second step, we used the data for 1980 to 1999 to calibrate two regression models, predicting lane miles as a function of road length, for rural and urban roads respectively (both adjusted R^2s = 0.996). We then used those equations to backcast lane miles for the years 1966 to 1979.

Other Variables Considered

Other variables were considered for this study, but were not included due either to measurement problems or time constraints or both. For example, we explored using transit passenger-miles as an additional dependent variable, since it has been suggested (Hamer, *et al*., 1992; Salomon, 1994) that telecommuters are more likely to reduce travel that may be more difficult to undertake, often meaning transit trips. Thus, it was conceivable that we could see a stronger effect of telecommuting on transit miles than on VMT. However, data before 1978 included only commuter rail, whereas later years included bus, light rail, heavy rail, trolley, ferry, and other transit modes. This resulted in an abrupt discontinuity in the trend (and furthermore, data for 1975 and 1976 were not readily available). In order to maintain longer time series for the remaining variables (which, even so, span only a scant 34 years as noted earlier), we decided not to include this variable in the study. For other variables such as real personal consumption expenditures and national and personal income, data were available but appeared to be sufficiently similar to other variables already included, that in the interests of time we chose not to explore them further. Future work of this nature could consider the inclusion of additional variables to explain more of the variation in VMT.

4.3 Measuring the Amount of Telecommuting

A number of organizations have produced estimates of the amount of telecommuting or home-based work in the US from time to time. In this section we first discuss some of the key issues associated with measuring telecommuting, and then assess the available data in view of those key issues.

4.3.1 How Many Telecommuters are there?

At least three dimensions are important in evaluating the suitability of the available data for the purposes of this study: definition, quality, and quantity. We address each of these in turn.

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[3] The lowest adjusted R^2 in this set of equations was 0.67, for rural major collectors. This category accounts for 13-14% of total rural lane miles. Two other adjusted R^2s were 0.91 and 0.95; all others were 0.99 or higher.

4.3.1.1 Who is a Telecommuter?

The lack of a concise and universally-accepted definition of telecommuting has confounded research and policy-making since the 1970s. The use of inconsistent, unclear, or unsatisfactory definitions by different studies has resulted in a fundamental ambiguity with respect to the importance of the phenomenon. Very narrow definitions suggest that telecommuting may be of marginal value as a travel demand management (TDM) strategy, whereas broad definitions lead to the natural question: If so many are telecommuting, where is the reduction in congestion?

In the most strict and narrow definition, telecommuting is *the performance of work at home or in a telecenter, using information technology, which substitutes for a commuting trip*. More loosely, telecommuting is sometimes defined simply as *working at home (or in a telecenter).* And at the broadest extreme, telecommuting is sometimes used interchangeably with teleworking (and a broader definition of teleworking than the one offered in the Introduction to this report) to refer to *using information technology to perform work "at a distance"*. Clearly, both of the latter definitions include many situations in which travel either is not affected (overtime work from home; home-based self-employment for which the alternative is not working at all; ordinary uses of fax, e-mail, and telephone to reach distant parties) or is actually facilitated (use of mobile phones and laptops to support work while traveling). Thus, from the perspective of understanding the potential of telecommuting to *reduce* travel or fuel consumption, the definition of telecommuting should be closer to the narrow end of the spectrum.[4]

To our knowledge, all the sources measuring telecommuting at the aggregate level focus on home-based telecommuting. This is not a major concern, since center-based telecommuters in the US probably number only in the hundreds (Stanek and Mokhtarian, 1998). Thus, the discussion below will be restricted to home-based work.

In evaluating sources measuring the amount of home-based work, several questions need to be asked with respect to the reported numbers:

- **What kind of worker is being counted?** If the types of occupations being measured are not restricted, counts of home-based workers will include farm workers, live-in domestic workers, and self-employed service workers in occupations such as child care, plumbing, and so on. It would perhaps be appropriate to restrict the count to information workers, but (a) even non-information workers can legitimately telecommute – replace a commute trip – to some extent (Mokhtarian, 1998); and (b) categorizing each occupation as representing information work or not is far from straightforward.

- **What is the threshold frequency for being counted?** Obviously, there will appear to be a lot more telecommuters if the criterion is telecommuting "at least once a month", than if the criterion is doing it "at least three days a week".

[4] As discussed in the Introduction, however, it is also desirable, albeit beyond the scope of the present study, to analyze the overall impact of telecommunications on travel – including the ways in which it may increase travel as well as decrease it.

- **What other criteria are applied?** Some surveys try to screen out inappropriate respondents (e.g., homemakers or uncompensated employees of a family business) by asking if they conduct "paid work at home". This can have several problems:

  - The "paid work" may be a moonlighting job, undertaken in addition to a regular job involving commuting. In that case it would be erroneous to consider the respondent a telecommuter.

  - A respondent may interpret the question as referring to being paid explicitly and directly for work done specifically at home. As a professional being paid a fixed salary rather than an hourly wage, he may not consider work at home to be "paid work" *per se* and hence erroneously not be counted as a telecommuter. Deming (1994) distinguished between working at home "for pay" (including salaried telecommuters as well as self-employed home workers), and "taking work home" which he classified as "unpaid". It is likely that many respondents to a question about working at home for pay would not make that distinction unless it is carefully drawn for them.

    In commenting on definitional differences between its 1986 and 1987 National Work-at-Home Surveys, the LINK Resources (undated, p. iv) marketing research firm remarked that, "In summary, self-employed homeworkers and home business operators probably tended to respond more to the 1986 phrase: 'income-producing work-at-home', while corporate homeworkers probably tended to respond more to the 1987 phrase, 'job-related work-at-home'. Thus, the balance between self-employed and corporate homeworkers shifted significantly toward the latter in 1987, more so than would be projected from the 1986 base data."

  - On the other hand, if a salaried professional *does* consider her work at home to be "paid work", but only works *overtime* at home without eliminating any commute trips, she could be erroneously *counted* as a telecommuter.

  Another criterion sometimes applied is to ask whether the individual works at home under a "formal arrangement" with the employer. This screen seems likely to miss the considerable amount of irregular and ad hoc telecommuting that occurs, and even many regular telecommuters may not consider themselves to have a formal arrangement (Dannhauser, 1999; for example, there may be nothing in writing indicating such an arrangement, no prior training, no special reporting requirements).

A final important question to ask is:

- **What forms of employment are being counted?** Specifically, does the count include home-based business workers, salaried employees, or both? As discussed in the Introduction, the transportation impacts of home-based business workers are more ambiguous than those of salaried employees who telecommute. Some surveys include additional categories, such as contract workers. The latter are generally technically self-employed, but have a long-term arrangement with one or a small number of clients for whom they may act almost as an employee. In the empirical analysis conducted here, we include contract workers among the count of telecommuters, in the belief that contract workers are more similar to salaried employees than to independently self-employed workers in their commute and other travel patterns.

4.3.1.2 Quality and Quantity of Telecommuting Data

Aside from the central question of how telecommuting is defined, it is also important to consider the quality and quantity of data available from a given source. With respect to *quality*, some questions to ask are:

- **On what size sample are the numbers based?** All else equal, a larger sample produces more precise estimates of the characteristic of interest than does a smaller sample. In a survey of home-based work, it is sometimes not clear if the reported sample size is based on the entire sample of conventional as well as home-based workers, from which the proportion of home-based workers can be estimated, or whether it represents the number of home-based workers in the sample. In the former situation, clearly the number of home-based workers will be considerably smaller than the reported sample size, which means that the estimates of characteristics of home-based workers will be less precise than the published sample size would suggest.

- **Was the sample properly drawn and weighted to be representative of the population?** On the other hand, unless the sample is properly handled, even a very large sample can be unrepresentative of the population of interest, and therefore inferior to a smaller sample that *is* representative. Unfortunately, the procedures by which the sample was drawn and weighted are often not presented, and thus it can be difficult to judge the reliability of the sample. The fact that organizations that collect statistics on a regular basis frequently report revised estimates a year or two later is evidence that, for example, the proper weighting for a sample can be open to judgment and capable of improvement. Such practices leave one wondering whether estimates that remain unrevised do so because they are "right" (or as "right" as they can be made) – or only because they haven't been as carefully examined as those that *are* revised.

- **Could the results have been influenced by external considerations?** The individuals who are counting home-based workers are human beings living in a social context for their work, not completely impartial machines performing a neutral and exact calculation. As such, all humans bring an element of subjectivity to the task at hand. In the current context, there may be a number of forces at work to bias upward the published forecasts of telecommuting (Salomon, 1998). It should be emphasized that the effect of these forces on any given individual may be conscious or unconscious:

    - Widely-publicized statements of key opinion leaders have predicted major increases in remote work, and it can be difficult to "buck the current". For example, management expert Peter Drucker claimed in 1989 that "[i]n 20 years Japanese office workers may still commute … to downtown office towers. But no one else in the developed world will… [C]ommuting to office work is obsolete" (Drucker, 1989, p. 38)[5]. More recently, the senior and respected statistician Norman H. Nie predicted that, "by 2005, at least 25 percent of the American workforce will be telecommuters or home office workers" (1999, p. 50).

- When putatively neutral government agencies include predictions of major increases in their reports (e.g., US DOE, 1994), it may invest those predictions (sometimes made by other interested parties) with greater weight.

- When the same numbers or predictions (whether quantitative or qualitative) are repeatedly cited in a variety of contexts, they take on the aura of "conventional wisdom" and tend to be accepted more and more readily.

- Often the predictions are made or sponsored by a party with a vested interest in promulgating a higher number. Such predictions are not wrong simply because of that fact, but they should be viewed with considerable caution.

- The media are oriented toward reporting unusual events or novel ideas rather than the typical, and so they are likely to invest evidence of a new trend with greater weight than is warranted.[6]

- **Are the results plausible?** One way to help counter the inevitable lack of objectivity discussed above is to subject results to a separate reality check. If a certain result has logical implications that are not credible, then clearly the legitimacy of the result is open to question.

With respect to *quantity* the question is simply:

- **For how many years are comparable counts available?** Since we are conducting a time series analysis, it is important to have a series of data for as many years as possible, with the variable of interest defined consistently across time.

4.3.1.3 Evaluation of Available Sources

Four different sources of published data on the number of home-based workers in the US were identified for this study. Table 2 summarizes the important information about each source. The source labeled "market research firms" refers to a series of annual surveys of home-based work directed by a single individual, Thomas E. Miller, under the auspices of several different firms over time: LINK Resources, FIND/SVP, and Cyber Dialogue.

5 In fairness, in the same article (p. 38) Drucker commented that "Contrary to what futurists predicted 25 years ago, the trend is not toward individuals working in their homes." His focus was on the decentralization of office work from high-density downtown business districts. However, "sound bites" such as "commuting to office work is obsolete", coming from an acknowledged expert, lodge in the public consciousness and have often been cited in support of the telecommuting phenomenon.

6 Conversely, once the "new trend" becomes commonplace, they are likely to overreport evidence of a backlash or retrenchment or yet a different trend, as indicated by several recent articles suggesting that telecommuting "isn't working" (Armour, 2001; Garber, 2001).

One immediate observation from the table is the disparity in definitions of what is being counted by each source. This doubtless contributes to the wide range of numbers for years in which there is more than one estimate. For example, in 1997 the Bureau of Labor Statistics reported 3.6 million home-based wage and salary workers (based on the Current Population Survey), whereas the market research firm of FIND/SVP estimated there to be 11.1 million telecommuters. But the CPS data counted only "formal arrangements" of home-based wage and salary work, which as indicated above is likely to undercount the number of telecommuters. On the other hand, the FIND/SVP survey included contract workers as well as salaried employees in its total. Excluding the 3.4 million reported contract workers from that total (leaving 7.7 million salaried telecommuters) and hypothetically inflating the CPS number to correct for a downward bias would bring the two counts closer together, although the discrepancy between 3.6 and 7.7 million is probably larger than would be accounted for by a CPS undercount alone.

Key issues associated with each source can be briefly summarized as follows:

US Census Bureau: The decennial census counts only those who worked at home most of the preceding week, so it undercounts telecommuters by excluding those who do so less than three days a week (which is probably the majority of telecommuters). On the other hand, it includes farm, domestic, and service workers whose home-based work does not replace a commute, so in that respect it is an overcount (Handy and Mokhtarian, 1995; Pratt, 2000). The net effect of these two counteracting biases is uncertain. In any case, Census data are available only for decennial years, which further limits its suitability for this study. It is interesting, however, that the proportion of the employed labor force working at home by this definition stands at 3% in both 1990 and 2000, indicating that this segment of home-based work is not increasing beyond the normal growth in the population.

Current Population Survey (CPS) of the Bureau of Labor Statistics (BLS): As mentioned above, this source probably undercounts telecommuters by focusing on those with "formal arrangements". Nie (1999, p. 50) says that the 1997 estimate "is likely to be low by as much as 1 million, because of the ambiguity of their telecommuting question." Also, data are available only for 1991 and 1997.

Market research firms: This represents the longest series of data on number of telecommuters, with estimates available each year between 1988 and 1998. The estimates are based on 2,000 – 2,500 randomly-selected households interviewed by telephone each year. Individual observations are presumably weighted to reflect national distributions on key variables.

Table 2: Summary of Data Sources for Number of Telecommuters

Data Source	Year	Count of Home Workers (millions)	Sample Size	Who Measured	Frequency Threshold	Nature of Arrange-ment	Form of Employment
US Census	1980	2.2 (2.3% of total emp.)	one in six US households	all workers 16 and over	most of previous week	any	salaried and self-employed
	1990	3.4 (3% of total emp.)					
	2000	3% of total emp.					
Current Population Survey	1991	1.9	~60,000 households	non-farm workers age 16 and over	none (30% worked at home 8 hrs/wk or more)	any	wage and salary
	1997	3.6	~50,000 households	non-farm workers age 16 and over		formal	salaried and self-employed, doing some work at home for primary job
Market Research Firms: LINK Resources	1988	2.2			none		company employees
LINK Resources	1989	3.0			none		salaried employees
LINK Resources	1990	4.0	2,500 total households		none		company employees
LINK Resources	1991	5.5	2,500 total households, 176 total telecommuters	all occupations (assumed)	none		company employees
LINK Resources	1992	6.6	2,500 total households	all occupations (assumed)	none	formal (3.1M), informal (3.5M)	company employees, including "conven-tional" (4.2M) and "contract-based" (2.4M)
LINK Resources	1993	7.3	2,500 total households		none		"pure corporate telecommuters" (5.12M) plus contract workers

(Table 2 continued)

Data Source	Year	Count of Home Workers (millions)	Sample Size	Who Measured	Frequency Threshold	Nature of Arrange-ment	Form of Employment
FIND/SVP	1994	9.1	2,000 total households		at least one day/month		corporate (6.6M) and contract workers (2.6M)
FIND/SVP	1995	8.5	1,200 total households		at least one day/month		conventional employees (5.4M) and contract workers (3.1M)
FIND/SVP	1996	9.7					conventional employees (6.5M) and contract workers (3.2M)
FIND/SVP	1997	11.1	2,000 total households		at least one day/month		conventional employees (7.7M) and contract workers (3.4M)
Cyber Dialogue	1998	15.7	2,000 Americans age 18 and older	all occupations (assumed)	at least one day/month	NR	full-time employees (7.4M), part-time employees (4.3 M), and contract workers (4.0M)
Telework America	1999	19.6	2,711 surveys; 247 tele-workers	18 years or older, head of household, all occupations	at least one day/month		employees (78%) and independent contractors (22%)
	2000	10.3	1,877 households	18 years or older, all occupations (assumed), regularly employed home-based teleworkers	at least one day/month		employees (8.3M) and contract workers (2.0M)
	2001	18.5	1,170 households				"employees" (salaried, contract, and self-employed not distinguished)

Notes for Table 2 (blanks in main table mean no information available)

Data Source	Year	Information Sources	Notes
US Census	1980	Deming (1994)	
	1990	Deming (1994)	
	2000	*USA Today*, 8/6/2001	
Current Population Survey	1991	Deming (1994)	
	1997	Dannhauser (1999), Mariani (2000), www.bls.gov/news.release/homey.nws.htm, accessed 10/27/2001	Figure reported is "the number of wage-and-salary employees who said they did some telecommuting from home [for their primary job] and got paid for it" (Dannhauser, p. 53).
Market Research Firms: LINK Resources	1988	Braus (1993), "1991 Telecommuting Data from LINK Resources Corporation" (June 1991)	
LINK Resources	1989	Gordon (1990), "1991 Telecommuting Data from LINK Resources Corporation" (June 1991)	Telecommuters defined as "salaried employees doing work at home during normal business hours".
LINK Resources	1990	Braus (1993), Gordon (1990), "1991 Tele-commuting Data from LINK Resources Corporation" (June 1991)	Telecommuters defined as "salaried employees doing work at home during normal business hours". 3.6M in 1990 source changed to "4.0 million" in 1991 source.
LINK Resources	1991	Gordon (1991), *Urban Transportation Monitor* (1991), undated press release from LINK Resources received 7/15/1991, personal communication from T. Miller to P. L. Mokhtarian, 7/15/1991	Telecommuters defined as "company employees who work at home part- or full-time during normal business hours". Press release indicates 43% of telecommuters are in professional and executive occupations; "nearly one-fourth are in a variety of manual and low-tech jobs".
LINK Resources	1992	LINK Resources "1992 Home Office Fact Sheet"; personal communication from Thomas Miller to S. L. Handy, 3/8/93	Telecommuters defined as "company employees who work from home part- or full-time during normal business hours". Includes "contract-based" workers as well as "conventional employees". Of the 4.2M conventional employees, 1.83M moonlight and 2.36M do not.
LINK Resources	1993	Gordon (1993b, c); USDOT (2000)	Gordon (1993b) reported 7.5M; adjusted to 7.6M in Gordon (1993c); reported as 7.3M in USDOT (2000, p. 6).
FIND/SVP	1994	FIND/SVP (1995), Russell (1996), presentation made by Thomas Miller to Telecommute '94 conference, San Francisco, Oct. 25-27.	Sample size mentioned in 12/7/95 audioconference cited below.
FIND/SVP	1995	July 21, 1997 press release on etrg.findsvp.com/prls/pr97/telecomm.html, accessed 7/21/97; audioconference presentation of T. Miller to Telecommuting Advisory Council, 12/7/95	Telecommuters defined as those working for an outside employer but working at home during normal business hours at least one day/month. Commented that the frequency screen of one day/month was added in the last two years, but that the rest of the definition has been consistent throughout. Number of telecommuters placed at 8.1M in 12/7/95 audioconference; later updated to 8.5M.

(Notes for Table 2 continued)

Data Source	Year	Information Sources	Notes
FIND/SVP	1996	USDOT (2000); July 21, 1997 press release on etrg.findsvp.com/prls/pr97/telecomm.html, accessed 7/21/97	Number of telecommuters in 1996 originally placed at 8.7M (USDOT, 2000). In 1997, this number was revised to 9.7M. A later FIND/SVP document reporting on the 11.1M telecommuters estimated for 1997 (etrg.findsvp.com/prls/pr97/telecom.html, accessed 1/20/98) commented, "Only 8.5 million telecommuters were identified in the company's last major survey on the trend two years ago" – apparently downplaying the 1996 number.
FIND/SVP	1997	July 21, 1997 press release on etrg.findsvp.com/prls/pr97/telecomm.html, accessed 7/21/97; Gordon (1997); Gordon (1998)	Screening question: "Do you work at home during normal business hours one or more days a month?" Miller states same definition used in past FIND/SVP surveys. In Gordon (1998), Miller indicates that applying 1998 definitions to 1997 would yield a total of 10.5M telecommuters (6.9M full-time employees, 3.6M contract workers) rather than the 11.1M published number.
Cyber Dialogue	1998	Oct. 28, 1998 news release on www.cyberdialogue.com/news/releases/1998/10-28-sb-telecommuting.html, accessed July 19, 2001; Gordon (1998)	Exact definition of telecommuting used: "working at home for an outside employer during normal business hours a minimum of one day/month or more".
Telework America	1999	Pratt (1999) (survey conducted by Joanne Pratt in association with Thomas Miller), and personal communication with first author, 8/16/2002	Pratt (1999): "In this study, teleworkers, also called telecommuters, are defined overall as employees or independent contractors who work at least one day per month at home during normal business hours." Personal communication: includes multiple-job holders.
	2000	www.telecommute.org/twa2000/research_results_summary.shtml, accessed 12/8/2000 (survey conducted by Jack Nilles)	Number calculated from reported total of 16.5M "regularly employed teleworkers" x 0.93 (reported proportion who are home-based or home- and center-based) x [0.54 (reported proportion who are employees) + 0.13 (reported proportion who are contract workers)]. Source comments that the 2000 TWA survey differs from the 1999 one in focusing only on "regularly employed" teleworkers, whereas the 1999 study included "occasionally employed" people. However, it goes on to say that "if the growth rate found in the year 2000 study were applicable to the total number of teleworkers found in the 1999 study, that would imply a total of 23.6 million teleworkers nationwide." A later document posted to the ITAC web site ("Telecommuting (or Telework): Alive and Well or Fading Away?", www.telecommute.org/aboutitac/alive.sthm, accessed 8/20/2001) refers to the 23.6M figure, without reference to 16.5M. A jaundiced view of this information suggests that the sponsors initially wanted to apply a more rigorous (and therefore presumably considered more appropriate) definition in the 2000 study, but then did not want to publicize a result that was lower than in the 1999 study. If true, this is a classic example of the results (as publicized) being influenced by external considerations.

	2001	www.telecommute.org/twa/twa2001/newsrelease.htm (survey conducted by D. Davis and K. Polonko of Old Dominion University); Pratt, personal communication to first author (3/8/2002). The full report on the 2001 survey costs $499; the information provided here is based on the freely-available sources noted.	Reported total was 28.8M, which includes work done "on the road, in telework centers or in satellite offices." Table entry of 18.5M calculated from 28.8M x [0.217 (reported proportion working {only} from home) + 0.424 (reported proportion combining working at home with some other form of teleworking)]. However, since distinctions between forms of employment are not mentioned, the numbers probably include all teleworkers, not just salaried employees and contract workers. If salaried employees and contract workers comprised the same percentage of teleworkers in 2001 as they did in the 2000 TWA survey (67%), the relevant number of telecommuters in 2001 is 18.5 x 0.67 = 12.4 M. Pratt indicates that the 2001 number comparable to the 16.5M reported for 2000 is 15.8M. If 15.8M is deflated by the same factor of 0.62 used in the note above for the year 2000 (representing the proportion of the total who work from home and are salaried employees or contract workers), the result is 9.8M.

There are several concerns with the market research data:

- Since telecommuters represent a relatively small proportion of the total work-at-home population (other segments measured in the same survey include self-employed home workers, moonlighters, and those who only do overtime work at home), the projected number of telecommuters in the population is based on numbers much smaller than the total sample sizes in these studies. For example, the estimate of 5.5 million telecommuters in 1991 is projected from a sample of 176 telecommuters (personal communication of Tom Miller to P. L. Mokhtarian, 7/15/1991). Even the larger projections in later years must have been based on samples of around 200 or so. Estimating the population proportion of telecommuters from the sample proportion out of a total of 2,000 households can theoretically be done with a reasonable degree of accuracy. But that is true only under the assumption that the sample is properly weighted. As discussed above, this is by no means a cut-and-dried process, and there is much room for error. For example, FIND/SVP originally publicized the number of telecommuters in 1996 as 8.7 million, and later revised its estimate upward to 9.7 million (the number used in this analysis). Smaller corrections were also made to the numbers initially disseminated for 1990, 1993, and 1995.

- Moonlighters are theoretically counted in a separate category ("part-time self-employed homeworkers"). But, in a personal communication to Susan Handy (3/8/1993), Mr. Miller reported that among the 4.19 million conventional employees counted as telecommuters in 1992, 1.83 million (44%) were moonlighters. This raises the question as to whether some people in this category were incorrectly classified as telecommuters when in fact all their home-based work was conducted for their second job.

- The number of telecommuters estimated for 1998 was placed at 15.7 million. A press release on Cyber Dialogue's web site comments that this number comprises 7.4 million full-time employees, 4.0 million contract-based workers, and 4.3 million "part-time employees who telecommute informally". The latter segment was found to contain mostly "retirees and homemakers who are capitalizing on the full-employment economy to supplement income via home-based work. Almost three out of four of this segment are women, by far the highest ratio of the three telecommuting segments. This group was found to be very low-tech and much more a reflection of the strong economy than of PC and Internet adoption." It seems clear, then, that this segment of part-time informal telecommuters is for the most part not going to be reducing commute travel: the alternative for most of them is not "working at a conventional job", but rather "not working at all". We considered eliminating this group from the total, but ultimately decided not to do so because previous years' totals for conventional employees also included both full- and part-time employees without distinguishing them – and so eliminating part-time employees from the 1998 total only would have been inconsistent.

Telework America: The trade association International Telework Association and Council (ITAC) sponsored surveys of teleworking during "Telework America" (TWA) promotional weeks in 1999, 2000, and 2001. The surveys were conducted by different parties and differed in sampling procedure and definition of a telecommuter (see notes on Table 2). Because of these distinctions, it is difficult to compare the three numbers.

The estimated number of telecommuters for 1999 was 19.6 million (employees and independent contractors). It is not entirely clear why this number is so much higher than others for the same and nearby years. The survey director speculates that it may be due to the inclusion of multiple job holders whose home-based work is primarily for their second job (personal communication of J. H. Pratt to P. L. Mokhtarian, 8/16/2002).

The number of telecommuters estimated for TWA in 2000 (10.3 million) counted only the "regularly employed", and is much lower than the 1999 number – lower even than the 1997 and 1998 numbers (11.1[7] and 15.7 million) in the market research series. Further, using screens consistent with the year 2000 survey, the number of telecommuters in 2001 is estimated by us to be 10 - 12 million (see notes on Table 1). Placing the 2000 and 2001 TWA numbers in sequence with the market research series, and remembering that a more valid number for the 1998 Cyber Dialogue study would be 11.4 million (excluding the 4.3 million part-time informal telecommuters who were largely retirees and homemakers), suggests that the number of telecommuters has been fluctuating around 10-11 million for the five years 1997-2001. This observation, combined with the slight declines (or, relative stability) previously noted for the four AHS and CPS counts taken between 1997 and 2001, raises the question of whether that degree of penetration of telecommuting might constitute an equilibrium; at a minimum it suggests that telecommuting might be growing much more slowly now than in years past. Pratt (2002) raises a similar question, using different definitions for various forms of telework.

The conclusion from the above discussion is that none of these sources is entirely satisfactory, for various reasons. Ultimately, the necessity of having data measured reasonably consistently over a series of years dictated the choice of the market research series of numbers for this study. However, it should be stressed that these numbers, based as they are on small samples that must rely on the proper weighting in order to be representative, are in our opinion subject to a great deal of uncertainty. For one thing, although available information is sketchy, the definitions used in the surveys do appear to have evolved over the years (Gordon, 1998). Overall, the impression given by the concerns outlined above is that these data are likely to overcount the number of "true" telecommuters – those who will genuinely be reducing commute travel. Nie (1999, p. 50) also shares the belief that at least the 1998 estimate is "arguably too high because of their sampling methodology", although he does not elaborate.

To some extent it can be argued that errors in the absolute numbers are not so important, since errors operating in the same direction will tend to cancel out when assessing the change in telecommuting from year to year. On the other hand, if absolute numbers of telecommuters are overstated, it is possible that the true numbers of telecommuters would not be high enough to create a measurable impact on VMT, or that such an impact, even if measurable, would be harder to detect amidst the "noise" in the data.

[7] As indicated in the notes to Table 2, this number may actually be 10.5 million in terms of consistency with 1998 definitions.

4.3.2 How Often do they Telecommute?

So far, the discussion of measuring the amount of telecommuting has focused on the number of telecommuters. But Handy and Mokhtarian (1995) distinguish between telecommuting *penetration*, and *levels*. Penetration refers to the number of people who have adopted telecommuting, whereas level refers to the number of telecommuting occasions against some reference (such as number per day or per week, or percent of person-workdays on which telecommuting occurs). From the standpoint of understanding the impacts of telecommuting on VMT (as well as most other impacts, for that matter), it is clearly important to know the frequency or extent to which telecommuting is occurring, not just the number of people doing it at all, no matter how infrequently.

Data on the frequency of telecommuting is even less available than data on the number of telecommuters, and when it is available, it is subject to many of the same issues discussed with respect to number of telecommuters. In addition, data on telecommuting intensity, so to speak, is often gathered and/or presented in the form of number of hours per week that are worked at home. The translation of that form to number of commute trips eliminated is ambiguous. For example, if a telecommuter reports working 16 hours a week at home on average, that could constitute:

- two full 8-hour days for which the commute was eliminated;
- one 8-10-hour day for which the commute was eliminated, plus 6-8 hours of overtime work on days involving a normal commute and/or weekends;
- four days on which the individual worked at home for half the day but still made the commute (with one direction in the off-peak);
- 5-6 days on which the individual worked at home in the evenings after making the normal peak-period commute all five weekdays;

or any number of gradations in between (personal communication from T. E. Miller to P. L. Mokhtarian, 7/15/1991). Obviously the impacts on VMT and peak-period VMT vary widely among these alternatives. A further complication is that telecommuting often results in a rearrangement of the work schedule to suit personal needs, so that work on a telecommuting day may not occur during the conventional 8 a.m. – 5 p.m. window. Thus, when surveys report the proportion of time that a telecommuter works outside "normal working hours", it is not clear how much of that is replacing time in the regular office and how much is overtime supplementing a full day in the office.

The press releases and other reports associated with the marketing research numbers adopted for this study provide some information about telecommuting frequency, for several but not all of the years in the series. This information is generally in the form of average number of hours per week worked at home. This average ranges between 16.5 and 19, as reported for four of the 11 years in the series, with a frequency of 7-8 days/month (which translates to 1.6 – 1.8 days/week) reported for a fifth year. Importantly, for one year (1997), it was reported that the average hours per week worked at home was 18-19, with a median of 12. Thus, typical frequencies are lower than the arithmetic average suggests, which is skewed upward by a small proportion of very high frequency telecommuters.

To be included in the count for the marketing research studies, telecommuters needed to "work at home during normal business hours", at least one day a month. We can probably assume that one *full* day a month is meant (i.e. that for at least one day a month, the worker does not commute to the office at all). We generally know nothing beyond that about the number of days over which an average weekly number of hours of home-based work is spread, nor how many of those days (1) eliminate the commute altogether (full day telecommuting); (2) shift one or both legs of the commute out of the peak (partial day telecommuting); (3) do not affect the commute at all (overtime work at home). However, more information is available for one year. In 1995 (FIND/SVP, 1995), it was reported that "employee brings work home after hours" an average of 39.6 hours per month, while "employee telecommutes" 39.5 hours per month. With an average of 4.3 weeks per month, this suggests an average of 9 hours per week – one day a week or slightly more – spent in actual telecommuting, with a similar amount spent on after-hours work. This may be a typical result for the other years in which totals of 16.5 - 19 hours per week worked at home are reported.

The academic literature also contains some estimates of the average frequency of telecommuting. For example, Handy and Mokhtarian (1995) reported an average of 1.2 days per week, across eight different studies. Additional sources cited in Mokhtarian (1998) report average frequencies ranging between 0.9 and 1.4 days per week. Since the dates of these studies range from the late 1980s to mid-1990s, and include programs in the Netherlands and Australia as well as the US, they suggest a fair amount of spatial and temporal stability in typical telecommuting frequencies. One could reasonably hypothesize changes in either direction over time (Handy and Mokhtarian, 1996a). On the one hand, the early adopters of telecommuting studied in the literature may be more enthusiastic about telecommuting than the mainstream and thus average frequencies would decline as telecommuting spread. On the other hand, technological improvements and increased managerial acceptance may allow people to telecommute more often than is the case now. Both of these effects could occur simultaneously, and counteract each other to unknown degrees.

Given all the evidence, it seems reasonable to conclude that average frequencies of telecommuting are remaining rather stable over time. In view of that, as well as the lack of complete information on frequency for each year in the sample, we will assume the average frequency of telecommuting to be constant across the period of study. The implication of this assumption is that the number of telecommuters across time is directly proportional to the number of telecommuting occasions across time, and thus that using the number of telecommuters directly to explain VMT will be appropriate. The model will allow us to assess the change in annual VMT per telecommuter, which can then be translated to a change in VMT per telecommuting occasion based on an assumption about the average telecommuting frequency (and hence the number of occasions in a year). We will present the results for two such assumptions: 50 occasions per year (representing a frequency of about once a week, not including vacation weeks), and 75 occasions per year (about 1.5 days a week). We are reasonably confident that these two assumptions bracket the true average frequency of telecommuting *in terms of number of commute trips eliminated per week*, which is the relevant metric for this study.

4.4 Plots and Correlations of the Basic Data

Figure 1 plots the time series for each of the dependent and explanatory variables used in this study. It can be seen that, in their raw form, the variables under study have vastly different scales. For example, the percent of population living in suburban areas ranges only from 53 to 63%, whereas VMT ranges between 869 and 2,481 billion miles. Using the variables with their natural scales could result in some significant relationships being overlooked in the models. Thus, with one exception, all variables were standardized (expressed in terms of standard deviations from their mean) before proceeding further. The number of telecommuters variable was not standardized because (as mentioned in Section 5.1) the natural log transformation was the best way to achieve stationarity for its series, and standardizing it would have resulted in negative as well as positive deviations from the mean, with the negative numbers mapping to $-\infty$ under the log transformation.

Table 3 presents the substantial (> 0.5 in magnitude, and significant at $\alpha = 0.05$) pairwise Pearson correlations of each variable (in its raw form) with the others. It can be seen that the significant correlations are numerous and quite high. As discussed in Section 3.1 and can be seen from Figure 1, this is because nearly all of the variables studied exhibit noticeable (mostly upward) trends with time (i.e. are non-stationary), and hence the spurious correlation of each series with time is confounding any genuine correlation they may have with each other. In Section 5.1 we indicate that differencing each series (except telecommuters, where the log transformation was used) achieved stationarity, and so here we present a second table showing the pairwise correlations of all variables as they will be entered into the models. Table 4 shows that substantial correlations among the differenced or transformed series are fewer and smaller. Nevertheless, there are still many strong and significant relationships.

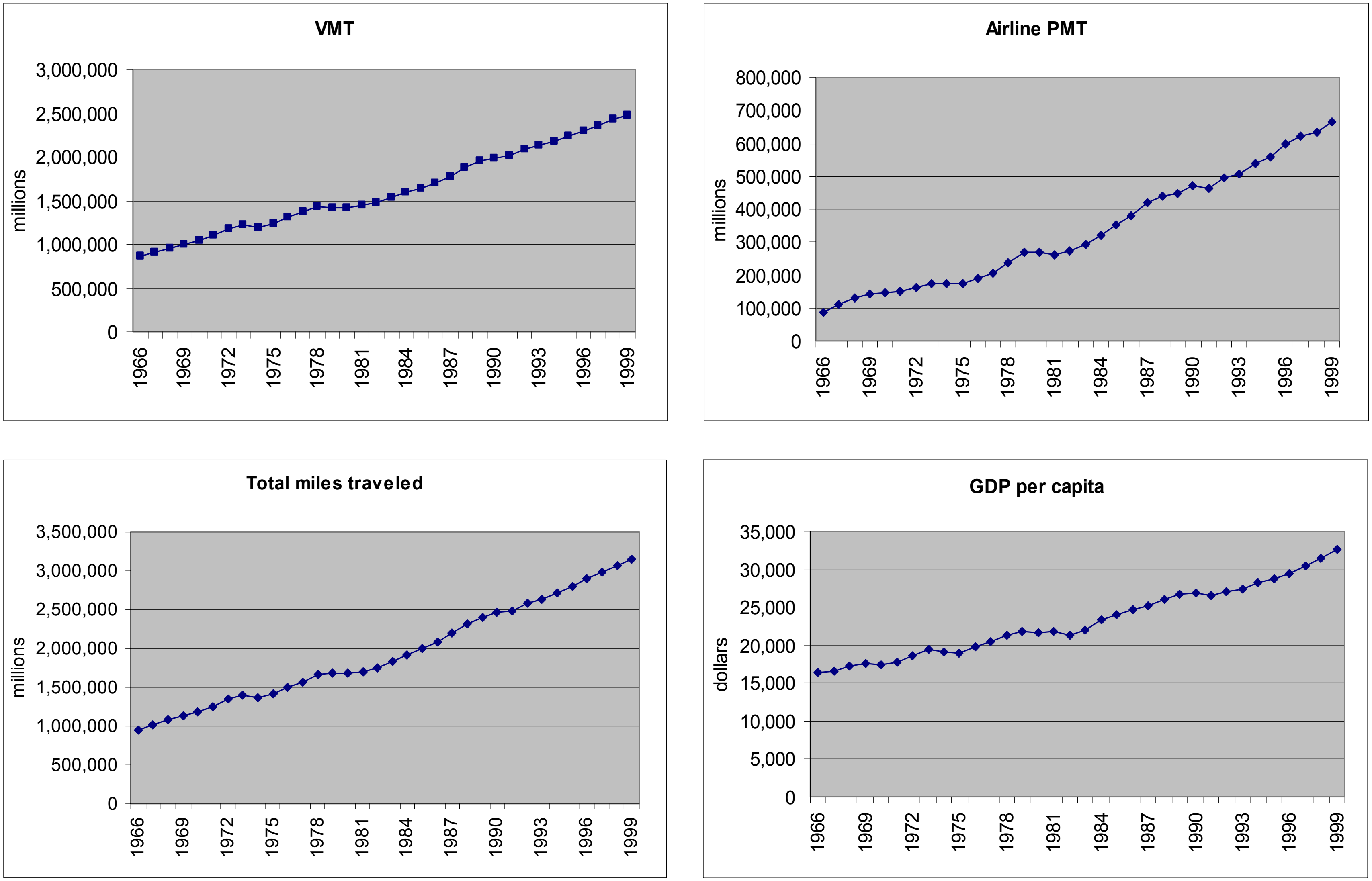
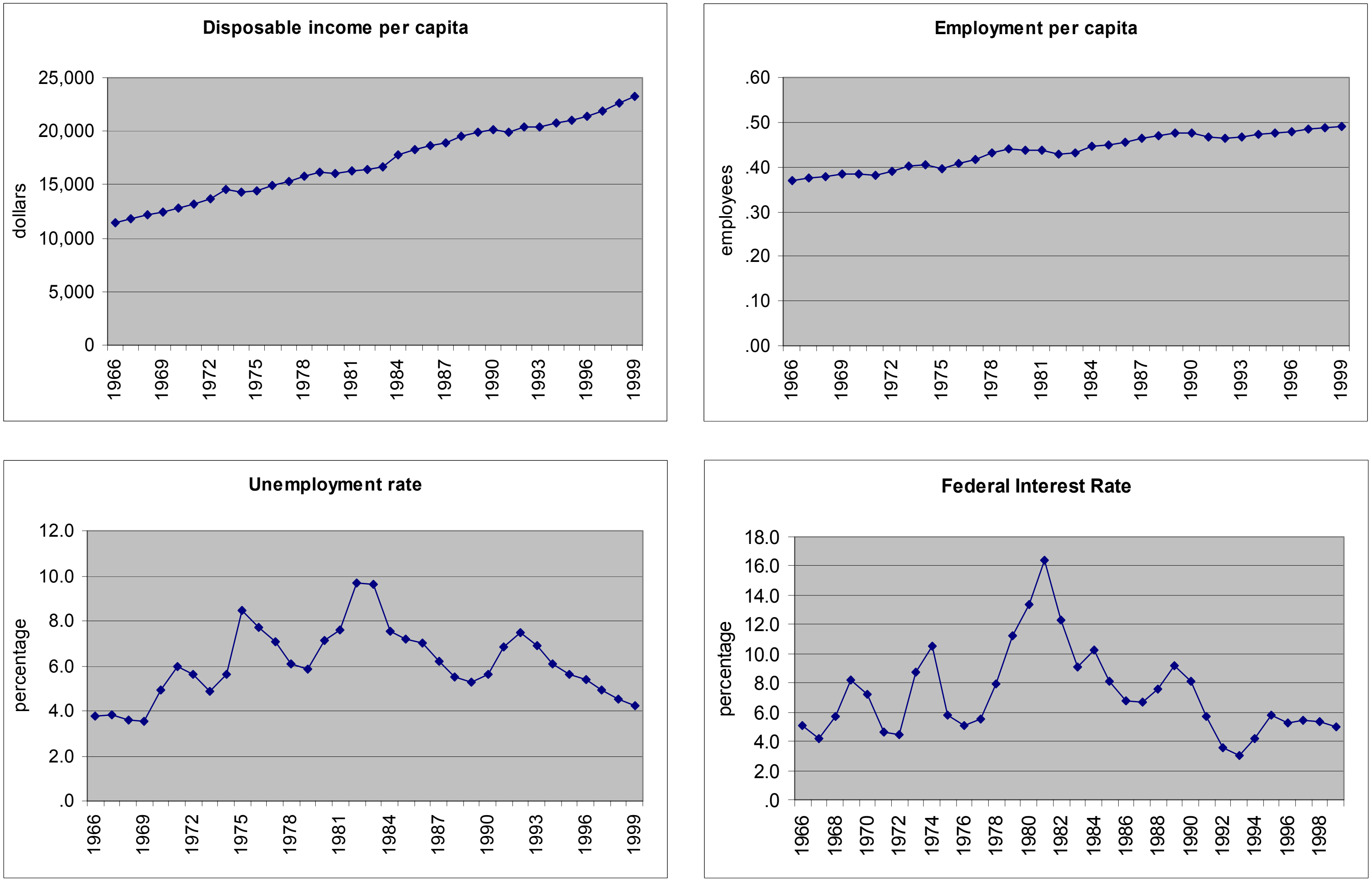
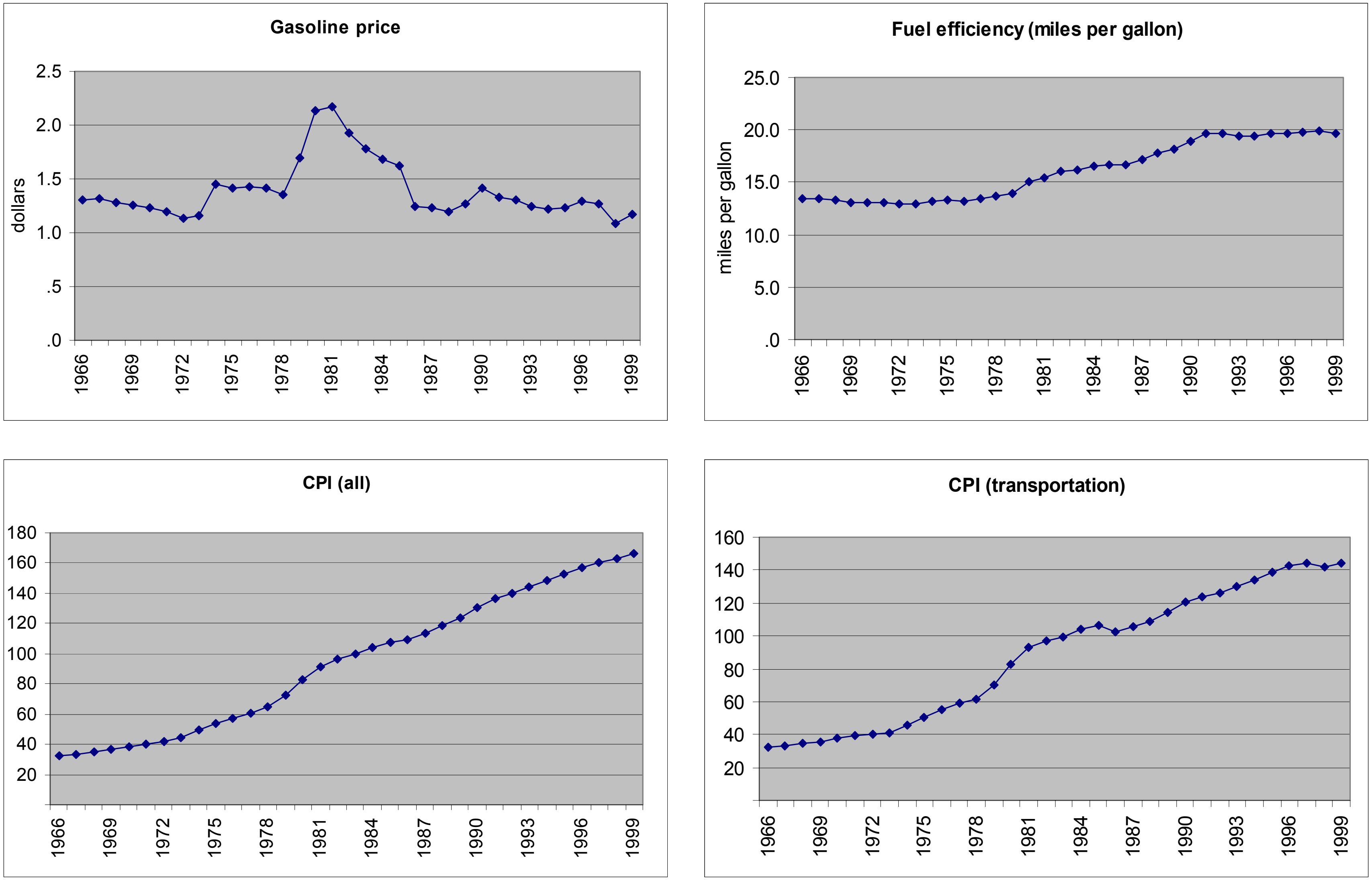


Figure 1: Time Trends of All Variables

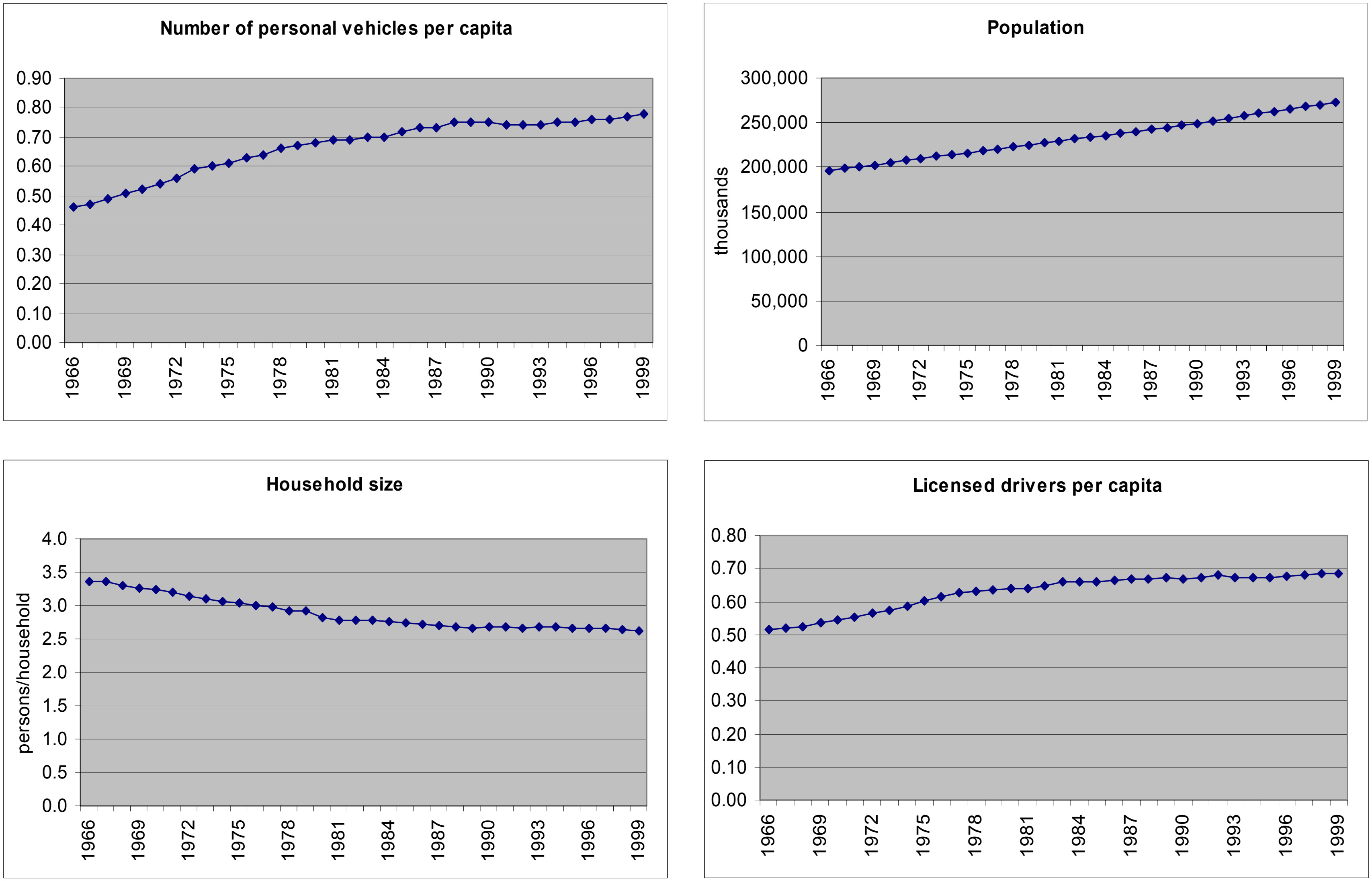
(Figure 1 continued)



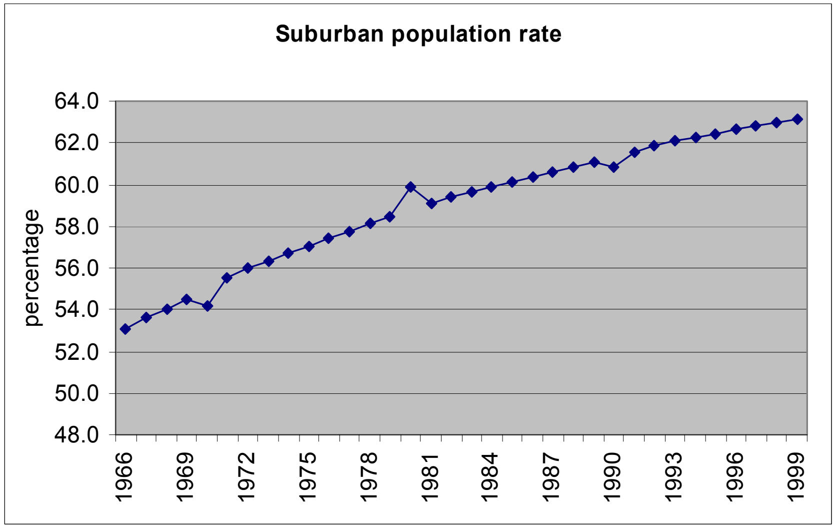
(Figure 1 continued)

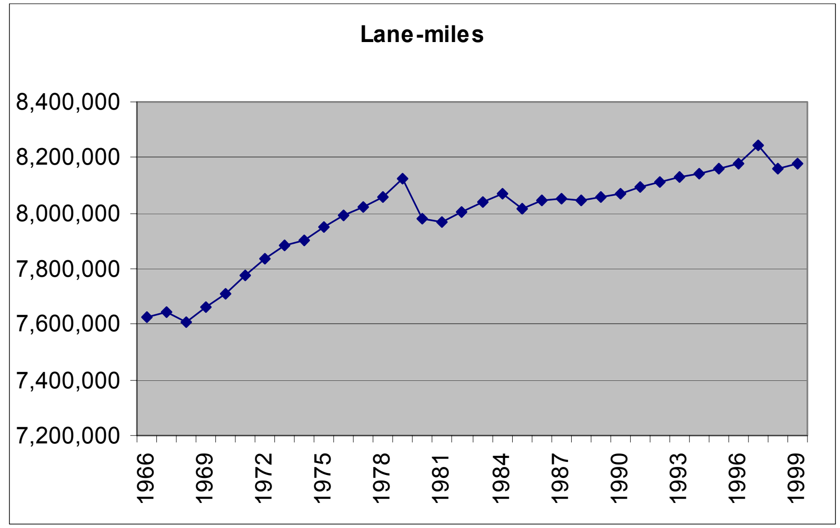


(Figure 1 continued)



(Figure 1 continued)





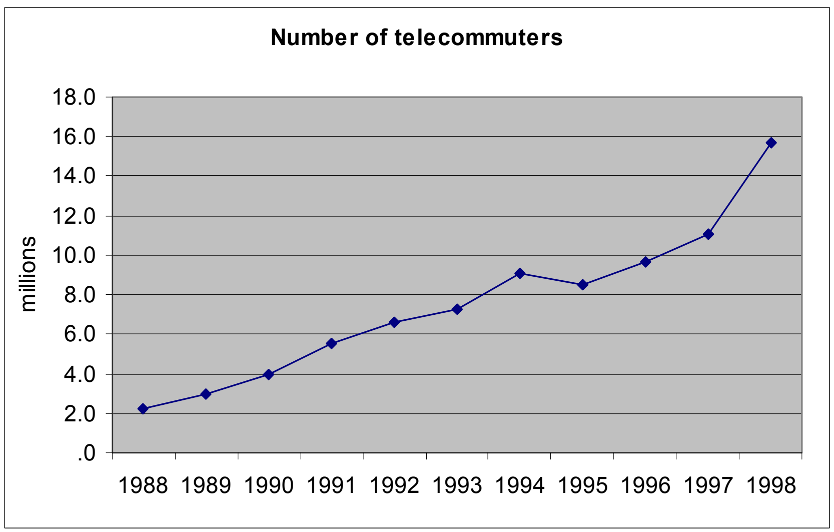


Table 3: Pairwise Correlation Coefficients (Raw Data)

Variables	VMT	Airline PMT	Total miles traveled	GDP per capita	Disposable income per capita	Employment per capita	Unemployment rate	Federal Interest Rate	Gasoline price	Miles per gallon	CPI (all)	CPI (transportation)	Population	Household size	Licensed drivers per capita	Number of personal vehicles per capita	Percent suburban population	Lane-miles	Number of telecommuters
VMT	1.000																		
Airline PMT	0.994	1.000																	
Total miles traveled	1.000	0.997	1.000																
GDP per capita	0.995	0.995	0.996	1.000															
Disposable income per capita	0.992	0.985	0.992	0.993	1.000														
Employment per capita	0.961	0.952	0.960	0.967	0.983	1.000													
Unemployment rate							1.000												
Federal Interest Rate								1.000											
Gasoline price							0.609	0.816	1.000										
Miles per gallon	0.956	0.964	0.960	0.950	0.950	0.924				1.000									
CPI (all)	0.985	0.985	0.986	0.982	0.986	0.966				0.981	1.000								
CPI (transportation)	0.969	0.967	0.970	0.966	0.977	0.967				0.975	0.996	1.000							
Population	0.995	0.989	0.995	0.991	0.994	0.970				0.960	0.994	0.985	1.000						
Household size	-0.909	-0.885	-0.904	-0.904	-0.944	-0.970				-0.876	-0.932	-0.948	-0.935	1.000					
Licensed drivers per capita	0.892	0.861	0.885	0.885	0.927	0.955				0.838	0.907	0.924	0.918	-0.991	1.000				
Number of personal vehicles per capita	0.916	0.890	0.911	0.913	0.949	0.973				0.861	0.926	0.939	0.938	-0.995	0.994	1.000			
Percent suburban population	0.962	0.943	0.958	0.955	0.978	0.978				0.917	0.968	0.973	0.978	-0.981	0.972	0.983	1.000		
Lane-miles	0.881	0.841	0.872	0.868	0.900	0.913				0.773	0.864	0.870	0.897	-0.932	0.960	0.955	0.942	1.000	
Number of telecommuters	0.969	0.949	0.965	0.949	0.970	0.641				0.781	0.947	0.896	0.962	-0.715	0.869	0.695	0.936	0.818	1.000

Note: Only correlation coefficients that are greater than 0.5 in absolute value and significant at α=0.05 are displayed.

Table 4: Pairwise Correlation Coefficients (Differenced or Transformed Data)

Variables	VMT	Airline PMT	Total miles traveled	GDP per capita	Disposable income per capita	Employment per capita	Unemployment rate	Federal Interest Rate	Gasoline price	Miles per gallon	CPI (all)	CPI (transportation)	Population	Household size	Licensed drivers per capita	Number of personal vehicles per capita	Percent suburban population	Lane-miles	Ln (number of telecommuters)
VMT	1.000																		
Airline PMT		1.000																	
Total miles traveled	0.935	0.687	1.000																
GDP per capita	0.588	0.601	0.695	1.000															
Disposable income per capita	0.603		0.636	0.818	1.000														
Employment per capita		0.501		0.768	0.612	1.000													
Unemployment rate		-0.591	-0.533	-0.872	-0.646	-0.877	1.000												
Federal Interest Rate						0.613	-0.528	1.000											
Gasoline price	-0.604		-0.532						1.000										
Miles per gallon										1.000									
CPI (all)									0.575	0.780	1.000								
CPI (transportation)									0.753	0.607	0.869	1.000							
Population													1.000						
Household size													0.528	1.000					
Licensed drivers per capita															1.000				
Number of personal vehicles per capita						0.504							-0.552	-0.593		1.000			
Percent suburban population																	1.000		
Lane-miles																		1.000	
Ln (number of telecommuters)										-0.662	-0.745	-0.608							1.000

Note: Only correlation coefficients that are greater than 0.5 in absolute value and significant at α=0.05 are displayed. All variables except number of telecommuters are first-differenced; the number of telecommuters is log-transformed.

4.5 Factor Analysis

Table 4 makes it clear that the explanatory variables may be strongly correlated, not only with the dependent variables, but with each other. This was somewhat by design, in that several alternate indicators of various hypothesized causal factors were selected as candidate explanatory variables. However, this could present some problems in developing the best multivariate model, since the magnitude, significance, and even sign of explanatory variables can change dramatically with the presence or absence of other highly correlated variables in the model.

One way to avoid the problems caused by multicollinearity among explanatory variables is to develop a smaller number of essentially uncorrelated composite measures, where each composite measure is some linear combination of the correlated variables. Factor analysis or principal components analysis (see, e.g., Rummel, 1970) are closely-related techniques for doing exactly that, and constitute one approach to dealing with multicollinearity that is advocated by econometricians (Greene, 1997; Kennedy, 1998). Specifically, factor analysis delineates patterns of common variation in a set of highly correlated variables, identifying a smaller number of (approximately) independent dimensions that contain the information common to the entire set.

We conducted factor analysis on the 15 (differenced) explanatory variables (other than number of telecommuters) used in this study. Using the eigenvalue-one cutoff rule, four factors were identified, accounting for 70% of the total variance in all the variables. In keeping with common practice, the initial solution was rotated (obliquely) to improve interpretability. Table 5 presents the pattern matrix of the resulting solution, where the magnitude of the ij-th cell of the matrix loosely represents the strength of the association of the i-th variable with the j-th factor. Thus, the construct represented by the factor can be inferred from the nature of the variables loading most strongly on it.

Table 5: Four-Factor Solution Pattern Matrix

Variable	Factor			
	Economic activity	Transportation cost	Demographics	Transportation supply
GDP per capita	0.880			
Disposable income per capita	0.688			
Employment per capita	0.899			
Unemployment rate	-0.968			
Federal Interest Rate	0.627	0.504		
Gasoline price		0.785		
Miles per gallon		0.475		
CPI (all)		0.815		
CPI (transportation)		0.919		
Population			0.579	
Household size			0.934	
Licensed drivers per capita			-0.453	0.578
Number of personal vehicles per capita			-0.713	
Percent suburban population			-0.414	
Lane-miles				0.724

Note: Principal Axis Factoring method was used for extraction. Only loadings greater than 0.4 in absolute value are shown.

The four factors identified in Table 5 are quite intuitive. The first one represents economic activity, with GDP per capita, disposable income per capita, employment per capita, unemployment rate (negative), and federal interest rate variables loading strongly on it. The second factor is labeled transportation cost, with heavily loading variables including gasoline price, CPI of all items, and CPI of transportation items. The third factor represents demographic trends, with strongly loading variables such as population, household size, and number of personal vehicles per capita. The fourth factor can be labeled transportation supply because it has the lane-miles variable loading most strongly on it (but the licensed drivers per capita variable also loads on this as well as the demographics factor). Table 6 shows that correlations among the factor dimensions are relatively low, as desired.

Table 6: Factor Correlation Matrix

Factor	Economic activity	Transportation cost	Demographics	Transportation supply
Economic activity	1.000			
Transportation cost	0.109	1.000		
Demographics	0.054	-0.082	1.000	
Transportation supply	-0.121	-0.267	-0.117	1.000

Since the fourth factor was dominated by the single supply measure of lane-miles, we also carried out another factor analysis without that variable. As shown in Table 7, the same remaining three factors (economic activity, transportation cost, and demographics) were identified, accounting for 67% of the total variance in the 14 variables. Those factors have essentially the same structure as before, except that the percent suburban population variable does not load strongly on any factor (highest loading of -0.342 on the demographics factor).

Table 7: Three-Factor Solution Pattern Matrix (without lane-miles variable)

Variable	Factor		
	Economic activity	Transportation cost	Demographics
GDP per capita	0.872		
Disposable income per capita	0.671		
Employment per capita	0.897		
Unemployment rate	-0.966		
Federal Interest Rate	0.644	0.487	
Gasoline price		0.739	
Miles per gallon		0.646	
CPI (all)		0.921	
CPI (transportation)		0.905	
Population			0.602
Household size			0.782
Licensed drivers per capita			-0.593
Number of personal vehicles per capita			-0.812
Percent suburban population			

Note: Principal Axis Factoring method was used for extraction. Only loadings greater than 0.4 in absolute value are shown.

Despite the intuitive nature of these factors, however, models incorporating the factor scores as explanatory variables were no better than, and generally inferior to, models containing only individual variables. In view of their disappointing performance and the additional complexity of interpretation involved with having composite factors as explanatory variables, we did not pursue this line of analysis further.

5. MODELING RESULTS

This section presents the results of the model-building process described in Section 3.3. The univariate analyses are presented in Section 5.1 below. With respect to the multivariate analyses, the first stage of the process is to model the dependent variable as completely as possible as a function of conventional variables *other* than telecommuting. The second stage is to model the residual unexplained portion of the dependent variable as a function of the number of telecommuters. In Sections 5.2-5.4 below, the first and second stage multivariate results are presented for each of the three dependent variables analyzed – ground VMT (passenger only, not freight), airline passenger miles (PMT), and ground VMT plus airline PMT (referred to as total miles traveled). As a general comment, we extensively explored including various lagged explanatory variables in the models, on the basis of both the univariate models described in Section 5.1 and the cross-correlation function of each explanatory variable with the dependent variable[8], but for the most part lagged terms were not significant in the final models presented here.

The econometric software package EViews 4.0 (Quantitative Micro Software, 2000) was used to estimate the models.

5.1 Univariate Analyses

The initial stage in the process is to ensure that each series is stationary, and then to develop univariate models resulting in white noise for the residuals. While it is essential that each series be stationary, the univariate models act more in an advisory capacity with respect to building the multivariate models. For example, if the univariate model for a given variable is AR(1), it suggests allowing a lagged as well as a contemporaneous term for that variable to enter the multivariate equation. However, as long as white noise is achieved for the residuals, the final multivariate equation can be streamlined to remove insignificant terms, in order to achieve parsimony and maximize degrees of freedom. Another reason for conducting the univariate analysis, though, is to offer models for predicting future values of the explanatory variables, simply as functions of their past history.

Visual inspection of the plots presented in Section 4, together with more formal diagnostic tools, revealed that all series under consideration in this study were initially non-stationary. However, in every case except one, first-order differencing of the series achieved stationarity. In the case of the telecommuting variable, a simple natural log transformation of the raw series sufficed. While using the log transformation for one variable and difference transformations for the others complicates the model interpretation slightly, the diagnostic statistics obtained for the differ-

[8] The cross-correlation function (CCF) displays the correlation of, say, VMT_t with a given explanatory variable X lagged 0, 1, 2, … time periods behind t, respectively. Spikes (high correlations) in the CCF at lag k suggest the inclusion of X_{t-k} in the model for VMT_t.

enced telecommuting series were not as strongly indicative of stationarity as they were for the log transform. Further, differencing the telecommuting series would have reduced the already small number of observations available for estimation from 11 to 10. We considered it preferable to preserve the additional degree of freedom, while maintaining a stronger basis for stationarity.

In many cases the differenced series immediately qualified as white noise, meaning that no further univariate modeling was necessary. In most of the remaining cases, modeling the differenced series as AR(1) achieved white noise, while in a few cases an AR(2) model was necessary. Table 8 lists each variable studied and the outcome of the univariate analyses.

Table 8: Univariate Time Series Models

Variable*	Univariate Model
Ground VMT	First-order difference only
Airline PMT	First-order difference only
Total miles traveled	AR(1) on first-order difference
GDP per capita	First-order difference only
Disposable income per capita	First-order difference only
Employment per capita	First-order difference only
Unemployment rate	First-order difference only
Federal Interest Rate	AR(2) on first-order difference
Gasoline price ($ per gallon)	First-order difference only
Fuel efficiency (miles per gallon)	AR(1) on first-order difference
Consumer Price Index (all)	AR(2) on first-order difference
CPI (transportation)	AR(1) on first-order difference
Population	AR(1) on first-order difference
Household size	First-order difference only
Licensed drivers per capita	AR(1) on first-order difference
Number of personal vehicles per capita	AR(1) on first-order difference
Percent suburban population	AR(1) on first-order difference
Lane-miles	First-order difference only
Number of telecommuters	AR(1) on natural log of raw observation

* As mentioned in Section 4, all variables except number of telecommuters were standardized before proceeding with the univariate analysis.

5.2 Multivariate Analysis: Ground VMT

5.2.1 First Stage Ground VMT Models (without Telecommuting)

Initially, we modeled (standardized, first-differenced) VMT itself, as a function (potentially) of the 15 explanatory variables (also standardized and first-differenced) shown in Table 8. Since population itself was seldom significant in those exploratory models, however, we also developed models of VMT on a per capita basis. After extensive testing of numerous different specifications of both forms of VMT, several good models emerged. We took each of these models to the second stage and examined the effects of telecommuting on the residual unexplained VMT in each case. It will be seen in Section 5.2.2 that the estimated effects of telecommuting depend substantially on which stage 1 specification is adopted. For this reason, we present a range of stage 1 models here. We recommend a model that in our opinion is best, and explain our reasoning, but we wished to show the reader the effects of various alternatives.

Table 9 presents three models for VMT and five models for VMT per capita. Adjusted R^2s for these models range from 0.488 to 0.649 (the latter being our recommended model)[9]. Because all variables are standardized, the magnitudes of the estimated coefficients can be viewed as direct indicators of the relative impact of the associated explanatory variable on the dependent variable.

Each of the models contains variables representing *economic activity* (GDP per capita in six models; disposable income per capita in the other two), *transportation price* (gasoline price in seven models; miles per gallon in five), or both. These kinds of variables are consistent with those found to significantly affect VMT in previous studies using linear (Springer and Resek, 1981) or log-linear models (Gately, 1990; Greene, 1992; Jones, 1993; Schimek, 1996). The "CPI-all" variable, which appears with a negative coefficient in five of our models, relates to both types of variables: it is both a measure of general economic conditions (the higher prices are in general, the less discretionary income people will have to devote to travel) and (due to its high correlation with CPI for transportation goods only: 0.87 between the two standardized, first-differenced variables) a proxy measure of transportation prices specifically. The final model in the table also includes CPI-transportation, with a counterintuitive positive sign, but it should be interpreted together with CPI-all and can be understood as a correction of the overly strong estimated impact of CPI-all. Based on the relative magnitudes of their coefficients, the combined impact of the two variables will nearly always be negative as expected.

The only other variable appearing in any of the models is population, which enters the VMT Alternative 3 model. Although this model is appealing (all variables having the expected sign, and an adjusted R^2 of 0.601), the coefficient of population is not significant at the 0.1 level (we chose this relatively liberal cutoff rather than the more typical 0.05, due to the small sample size). When population is dropped from the model, VMT Alternative 2 results, in which CPI-all then becomes insignificant at the 0.1 level. When CPI-all is dropped, miles/gallon becomes insignificant (not shown), finally resulting in VMT Alternative 1, the only case in which all variables (comprising only GDP per capita and gasoline price) were significant.

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9 The R^2s of 0.9 and higher that are frequently reported for time-series models are generally based on non-stationary series, where the high correlations of explanatory with dependent variables are due in large part to their mutual high correlation with time. As can be seen from the high pairwise correlations of our undifferenced data in Table 3, we would have obtained similarly high R^2s had our models been based on the raw data.

Table 9: Multivariate Time Series Models for Vehicle Miles Traveled (VMT) (N = 33)

Model	Adjusted R^2	Explanatory variables							
		Constant	GDP per capita	Disposable income per capita	Gasoline price	Miles per gallon	CPI (all)	CPI (transportation)	Population
VMT									
Alt. 1	0.555	0.0739 (7.930)	0.257 (3.968)		-0.0490 (-4.130)				
Alt. 2	0.582	0.0957 (4.291)	0.286 (4.249)		-0.0417 (-2.975)	0.181 (1.964)	-0.416 (-1.569)		
Alt. 3	0.601	0.0110 (0.186)	0.287 (4.366)		-0.0383 (-2.755)	0.204 (2.237)	-0.521 (-1.948)		0.916 (1.537)
VMT per capita									
Alt. 1	0.495	0.0663 (4.432)	0.332 (3.191)		-0.0761 (-4.000)				
Alt. 2	0.509	0.0521 (2.935)		0.472 (3.362)	-0.0658 (-3.354)				
Alt. 3	0.488	0.144 (3.814)		0.481 (3.282)		0.260 (1.781)	-1.226 (-3.135)		
Alt. 4	0.556	0.134 (3.884)	0.348 (3.333)		-0.0509 (-2.340)	0.298 (2.084)	-1.004 (-2.443)		
Alt. 5	0.649	0.153 (4.866)	0.366 (3.936)		-0.0936 (-3.847)	0.352 (2.737)	-2.076 (-3.990)	0.834 (2.895)	

Notes:
All dependent and explanatory variables are the standardized, first-order differenced (i.e.$X_t – X_{t-1}$) variables.
The number in parentheses indicates the t-statistic for that coefficient. The degrees of freedom are N-k where k is the number of parameters estimated, and hence ranges from 27 to 30 for these models. Critical t-values for α = 0.05 and 0.1, with 27 (30) degrees of freedom, are 2.052 (2.042) and 1.703 (1.697), respectively

Five models are presented with *VMT per capita* as the dependent variable. Alternative 1 is the counterpart to Alternative 1 for VMT only, but its goodness of fit is inferior. Alternatives 2 and 3 contain disposable income per capita instead of GDP per capita (the two variables being highly correlated), since the former variable may offer a more directly causal relationship to VMT per capita. However, their goodness of fit is also inferior to even the "worst" model of VMT alone.

Alternatives 4 and 5 represent the best models of VMT per capita, with Alternative 4 resulting from dropping the counterintuitively-signed CPI-transportation variable from Alternative 5[10]. But comparing the two models shows that (a) the jump in adjusted R^2 from 0.556 (Alt. 4) to 0.649 (Alt. 5) is rather extraordinary with the addition of just one variable, and (b) the addition of CPI-transportation results in lower standard errors of the estimators (and therefore higher t-statistics) in comparison to those in Alt. 4. This is an indication that excluding CPI-transportation would result in omitted variables bias. Excluding relevant variables that are correlated with included variables leads to biased coefficient estimates (where the bias is a function of the correlation between excluded and included variables) and also to upwardly biased estimates of standard errors. For these reasons, some authorities (e.g. Kennedy, 1998 and Conlisk, 1971) suggest that it is appropriate to retain two variables even when they are highly correlated and therefore their separate effects are difficult to distinguish, but to interpret only the combined effects of the two variables.

Thus, we advocate in favor of the Alternative 5 VMT per capita model as the final stage 1 model. It contains GDP per capita (positive impact on VMT per capita) representing economic activity, gasoline price (negative) and miles per gallon (positive) representing transportation prices, and CPI-all and CPI-transportation (joint impact negative), together representing both available income (inversely related) and transportation prices.

5.2.2 Second Stage Ground VMT Models: The Impact of Telecommuting

Table 10 presents the second stage models, identifying the impact of telecommuting on the residual VMT after the impacts of the stage 1 variables are accounted for. As a general tendency, it can be seen that the higher the adjusted R^2 in the stage 1 model, the lower the adjusted R^2 in stage 2. Further, the more powerful the stage 1 model, generally the smaller in magnitude and significance is the telecommuting coefficient in the stage 2 model. These are natural results: the more variance in VMT that is explained by the earlier variables, the less that remains for telecommuting to explain, and the less powerful it will be.

As indicated in Section 3.2, the scientific, conservative approach taken in this study is to attempt to disprove any effect of telecommuting, by explaining as much variance in VMT as possible using more conventional variables. It is noteworthy, then, that in all eight stage 2 models shown in Table 10, even the one based on the strongest stage 1 model, the telecommuting variable is significant at a 0.1 level or better. In particular, in the Alternative 5 VMT per capita model (our recommended stage 1 model), the estimated coefficient of the telecommuting variable has a p-

[10] Dropping CPI-all from Alternative 5, in the hope that CPI-transportation would change signs to reflect the combined impact of the two measures, resulted in a CPI-transportation coefficient with a p-value of 0.95 and a miles per gallon coefficient with a p-value of 0.77. Dropping both of these variables results in Alternative 1 of the VMT per capita group.

value of 0.057 (and the expected negative sign, meaning that increases in the number of telecommuters result in decreased per-capita VMT).

Table 10: Telecommuting Models for Residuals of VMT Models (N = 11)

Model	Adjusted R^2	Explanatory variables	
		Constant	Natural log of the number of telecommuters (in millions)
VMT			
Alt. 1	0.550	0.0988 (4.073)	-0.0450 (-3.636)
Alt. 2	0.289	0.0754 (2.643)	-0.0328 (-2.250)
Alt. 3	0.319	0.0731 (2.452)	-0.0363 (-2.383)
VMT per capita			
Alt. 1	0.628	0.143 (3.945)	-0.0781 (-4.232)
Alt. 2	0.591	0.136 (3.888)	-0.0703 (-3.934)
Alt. 3	0.410	0.118 (3.009)	-0.0566 (-2.818)
Alt. 4	0.438	0.118 (2.829)	-0.0632 (-2.968)
Alt. 5	0.273	0.102 (2.284)	-0.0499 (-2.183)

Notes:
Each dependent variable comprises the residuals of the corresponding estimated time series model in Table 9.
The number in parentheses indicates the t-statistic for that coefficient. Critical t-values for $\alpha = 0.05$ and 0.1, with 9 degrees of freedom, are 2.262 and 1.833, respectively.

Statistical significance is one critical measure of the importance of a variable, but practical impact is at least as critical a measure. A variable can be statistically significant but practically unimportant, and conversely a variable that is insignificant (perhaps due to a small sample, insufficient variation in the sample, and/or multicollinearity) can have an impact that is still potentially substantial, even if imprecisely estimated. In the present context, it is important to translate the estimated coefficient of the telecommuting variable into what it means in terms of impact on VMT.

Those impacts are displayed in Tables 11 and 12 for 1998, the last year in the time series on the number of telecommuters. Table 11 is based on the 95% confidence interval for the telecommuting coefficient, while Table 12 is based on the 90% confidence interval. To obtain the absolute impacts on VMT, the log of 15.7 (the number of telecommuters in millions, in 1998) is multiplied by the lower bound, midpoint, and upper bound of the confidence interval on the coefficient of log-telecommuters. Since VMT is standardized in the model, this gives the range of impacts of telecommuting on VMT expressed in standard deviations. The three numbers representing the range are then multiplied by the standard deviation of VMT (across the entire series, i.e. the factor used to standardize the observations in the series) to yield the incremental impacts of telecommuting in terms of absolute changes in VMT (an identical process based on VMT per capita is employed for the second group of models).

Next, to put the absolute changes in perspective, we express them as a percent of the total annual observed VMT (or VMT per capita) in 1998[11]. We also express them in terms of change in annual VMT per telecommuter. Finally, as a reality check, we calculate the estimated impact on VMT per telecommuting occasion, under two assumptions: 50 occasions per telecommuter per year (about one day a week) and 75 occasions per person per year (about 1.5 days per week). As discussed in Section 4.3.2, these two assumptions probably bracket the true mean frequency of telecommuting in terms of number of commute trips eliminated. Obviously, given a fixed total reduction in VMT, the higher the number of telecommuting occasions per year, the lower the average reduction in VMT per occasion.

Turning first to the 95% confidence interval results shown in Table 11, we note that the estimated mean percent changes in VMT are all reductions (as the uniformly negative coefficient estimates guarantee). The numbers indicate that estimated VMT without telecommuting would have been 1.78% to 3.31% higher than the observed VMT, with a mean impact of 2.12% implied by our recommended Alternative 5 VMT per capita model. Even the lower end of that range seems rather high, when comparing the impact of telecommuting to those of other transportation demand management (TDM) strategies. Thus, it is important to keep in mind the uncertainty associated with a point estimate of the impact, and to analyze the confidence interval around that point estimate.

Loosely speaking, the 95% confidence intervals displayed in Table 11 mean that, if the given model specification is correct, we can be 95% confident that the true mean effect of telecommuting on VMT lies somewhere in that interval. We would not be able to reject the null hypothesis that the true mean effect was any given point in that interval. With that in mind, the endpoints of the intervals shown in Table 11 enclose VMT changes from a 5.08% reduction to a 0.08% increase, where the latter can be interpreted as essentially no change. Importantly, the latter is the upper bound on the telecommuting impact for the preferred Alternative 5 model.

Assessing the per-occasion impact of telecommuting on VMT provides a useful concrete interpretation of the results. Looking first at the midpoints, we see that the models imply an average per-occasion reduction in VMT ranging between 55 and 102 miles for one-day-a-week frequencies, and between 37 and 68 miles for 1.5-day-a-week frequencies. To put these numbers in perspective, several benchmarks can be noted:

- Based on the 1995 NPTS, the average one-way commute distance in the US is 11.6 person-miles (Table 4 of Hu and Young, 1999). It is likely that the average commute length for the population of prospective telecommuters is longer than that, since other evidence suggests that telecommuters will be disproportionately drawn from workers having higher-than-

[11] Thus, strictly speaking, the percents presented are not "percent reductions in VMT", which would be based on [number of miles reduced/(miles reduced + miles observed)] instead of just [number of miles reduced/number of miles observed]. We preferred to report percent impacts based on observed VMT rather than on the estimated "counterfactual" VMT in the absence of telecommuting. However, in view of the relatively small reductions in question, the two ways of calculating percentages are not very different.

average incomes and professional, technical, or managerial occupations – both of which characteristics are related to longer commutes. Further, it has been noted that average commute lengths for the telecommuters in early empirical studies are longer than normal, although it is also suggested that that average is likely to approach (but not converge to) the typical average as telecommuting moves more into the mainstream (Mokhtarian, *et al.*, 1995).

- Also based on the 1995 NPTS, daily per capita PMT for people between 21 and 65 years old is 45-46 miles (Table 13 of Hu and Young). PMT for the population of prospective telecommuters is likely to be greater than this number by an unknown amount, for the reasons given above. VMT, on the other hand, will be lower than the corresponding PMT.

- Mokhtarian (1998) reports a weighted average of 56 vehicle-miles traveled on non-telecommuting days and 33 vehicle-miles saved per telecommuting occasion, calculated for telecommuters across four empirical studies (total N = 192). The telecommuters analyzed in these studies (based on data collected from 1988 to 1996) should be considered early adopters who may not be typical of "mainstream" telecommuters. If the expectation is correct that average commute lengths of telecommuters decline the greater the number adopting, then the average non-telecommuting-day VMT and the per-occasion savings identified in these early studies are likely to represent ceilings on current numbers.

With these bases for comparison, the midpoint reductions implied by all the models appear to be unrealistically high – even the lowest one of 37 exceeds the probably high value of 33 vehicle-miles reduced observed in disaggregate studies. Obviously, the reductions implied by the lower bounds are even more extreme. The upper bounds, however, are more plausible: they range from reductions of 39 miles to increases of 2.4 miles per occasion for the lower telecommuting frequency, and from reductions of 32 miles to increases of 1.6 miles per occasion for the higher frequency. The preferred Alternative 5 model represents the higher end of those ranges in both cases.

The 90% confidence intervals shown in Table 12 are included for consistency with our standard of a p-value of 0.1 or lower for retaining a variable in the model. However, the 90% confidence intervals are of course narrower than the corresponding 95% intervals (it takes a larger interval to be 95% sure of including the true value than only to be 90% sure), and so they constitute a less rigorous test of the null hypothesis that telecommuting has no effect on VMT. None of the 90% intervals enclose the zero point. In particular, comparing the 95% and 90% confidence intervals for the preferred Alternative 5 model leads to the conclusion that (if this is the correct model specification) we can be 90% confident that telecommuting reduces VMT (by an amount as little as 0.34% of the observed travel), but not 95% confident that it does so.

Table 11: Estimated Impact of Telecommuting on VMT in 1998 (using the 95% confidence interval for the estimated coefficient of telecommuting)

Model		Change in annual VMT (millions of miles)			% change in annual VMT			Change in annual VMT per telecommuter (miles)			Change in VMT per occasion (miles)		
		Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
VMT													
Alt. 1	50 occasions/year	-96,537	-59,509	-22,481	-3.98	-2.45	-0.93	-6,149	-3,790	-1,432	-123.0	-75.8	-28.6
	75 occasions/year										-82.0	-50.5	-19.1
Alt. 2	50 occasions/year	-86,836	-43,300	235	-3.58	-1.78	0.01	-5,531	-2,758	15	-110.6	-55.2	0.3
	75 occasions/year										-73.7	-36.8	0.2
Alt. 3	50 occasions/year	-93,460	-47,941	-2,421	-3.85	-1.97	-0.10	-5,953	-3,054	-154	-119.1	-61.1	-3.1
	75 occasions/year										-79.4	-40.7	-2.1
VMT per capita			(miles)										
Alt. 1	50 occasions/year	-456	-297	-138	-5.08	-3.31	-1.54	-7,256	-4,607	-1,958	-157.1	-102.4	-47.7
	75 occasions/year										-104.8	-68.3	-31.8
Alt. 2	50 occasions/year	-422	-268	-114	-4.69	-2.98	-1.27	-7,856	-5,120	-2,383	-145.1	-92.1	-39.2
	75 occasions/year										-96.7	-61.4	-26.1
Alt. 3	50 occasions/year	-388	-215	-42	-4.32	-2.40	-0.47	-6,683	-3,707	-731	-133.7	-74.1	-14.6
	75 occasions/year										-89.1	-49.4	-9.7
Alt. 4	50 occasions/year	-424	-241	-57	-4.72	-2.68	-0.64	-7,296	-4,140	-984	-145.9	-82.8	-19.7
	75 occasions/year										-97.3	-55.2	-13.1
Alt. 5	50 occasions/year	-387	-190	7	-4.31	-2.12	0.08	-6,667	-3,274	119	-133.3	-65.5	2.4
	75 occasions/year										-88.9	-43.6	1.6

Notes:
A negative sign indicates a reduction in VMT, while a positive sign indicates an increase in VMT.
Based on 50 and 75 annual average telecommuting occasions, the change in VMT per occasion is calculated for each case.

Table 12: Estimated Impact of Telecommuting on VMT in 1998 (using the 90% confidence interval for the estimated coefficient of telecommuting)

Model		Change in annual VMT (millions of miles)			% change in annual VMT			Change in annual VMT per telecommuter (miles)			Change in VMT per occasion (miles)		
		Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
VMT													
Alt. 1	50 occasions/year	-89,514	-59,509	-29,504	-3.69	-2.45	-1.22	-5,702	-3,790	-1,879	-114.0	-75.8	-37.6
	75 occasions/year										-76.0	-50.5	-25.1
Alt. 2	50 occasions/year	-78,580	-43,300	-8,021	-3.24	-1.78	-0.33	-5,005	-2,758	-511	-100.1	-55.2	-10.2
	75 occasions/year										-66.7	-36.8	-6.8
Alt. 3	50 occasions/year	-84,826	-47,941	-11,055	-3.49	-1.97	-0.46	-5,403	-3,054	-704	-108.1	-61.1	-14.1
	75 occasions/year										-72.0	-40.7	-9.4
VMT per capita			(miles)										
Alt. 1	50 occasions/year	-426	-297	-169	-4.74	-3.31	-1.88	-6,754	-4,607	-2,460	-146.7	-102.4	-58.0
	75 occasions/year										-97.8	-68.3	-38.7
Alt. 2	50 occasions/year	-392	-268	-143	-4.37	-2.98	-1.59	-7,337	-5,120	-2,902	-135.1	-92.1	-49.2
	75 occasions/year										-90.0	-61.4	-32.8
Alt. 3	50 occasions/year	-355	-215	-75	-3.96	-2.40	-0.84	-6,119	-3,707	-1,295	-122.4	-74.1	-25.9
	75 occasions/year										-81.6	-49.4	-17.3
Alt. 4	50 occasions/year	-389	-241	-92	-4.33	-2.68	-1.02	-6,698	-4,140	-1,583	-134.0	-82.8	-31.7
	75 occasions/year										-89.3	-55.2	-21.1
Alt. 5	50 occasions/year	-350	-190	-30	-3.89	-2.12	-0.34	-6,023	-3,274	-524	-120.5	-65.5	-10.5
	75 occasions/year										-80.3	-43.6	-7.0

Notes:
A negative sign indicates a reduction in VMT, while a positive sign indicates an increase in VMT.
Based on 50 and 75 annual average telecommuting occasions, the change in VMT per occasion is calculated for each case.

5.3 Multivariate Analysis: Airline PMT

5.3.1 First Stage Airline PMT Models (without Telecommuting)

With airline PMT as the dependent variable, the model outcomes were relatively more straightforward. The best models for PMT and PMT per capita, respectively, are shown in Table 13. The same variables are significant in both models: GDP per capita (positive impact), and gasoline price lagged one year (negative impact). Since gas prices may not only be an indicator of the cost of automobile travel but may also partly reflect the cost of airline travel, the presence of this variable is logical. Both variables were also prominent in the models for ground VMT.

On the basis of its slightly higher adjusted R^2 (0.552), with no other important difference between the two models, the airline PMT per capita model is the preferred one.

Table 13: Multivariate Time Series Models for Airline Passenger Miles Traveled (PMT) (N = 32)

Model	Adjusted R^2	Explanatory variables		
		Constant	GDP per capita	Gasoline price (1st order lag)
Airline PMT	0.542	0.0696 (4.997)	0.265 (2.615)	-0.0672 (-3.618)
Airline PMT per capita	0.552	0.0655 (4.102)	0.285 (2.449)	-0.0827 (-3.882)

Notes:
All dependent and explanatory variables are the standardized, first-order differenced (i.e. $X_t – X_{t-1}$) variables.
The 1st order lagged variable means $(X_t – X_{t-1})_{-1}$, equal to $(X_{t-1} – X_{t-2})$.
The number in parentheses indicates the t-statistic for that coefficient. Critical t-values for $\alpha = 0.05$ and 0.1, with 29 degrees of freedom, are 2.045 and 1.699, respectively.

5.3.2 Second Stage Airline PMT Models: The Impact of Telecommuting

Table 14 presents the stage 2 models for the residuals of each of the models in Table 13. The models have two noteworthy features in common: relatively low adjusted R^2s (0.144 and 0.154, respectively) and positive but insignificant coefficients for the number of telecommuters variable (p-values of 0.329 and 0.612, respectively)[12]. Since the stage 1 adjusted R^2s were lower for these models than for the VMT models, one might have thought that the stage 2 adjusted R^2s would have been higher here. The fact that they were lower instead, and that the number of telecommuters variable was insignificant despite having the opportunity to explain more residual vari-

[12] Note the appearance of an additional explanatory variable in both of these models: the first-order lag of the residuals of the corresponding model. This variable was statistically significant for the (preferred) per capita model, but not very significant (p-value = 0.105) for the other model. Its inclusion was necessary in both cases, in order to obtain white noise residuals and reduce the Durbin-Watson statistic (a test of autocorrelated error terms) to a value consistent with no significant autocorrelation. In both cases, including the lagged residuals *improved* the significance of the telecommuting variable, i.e. telecommuting was even more insignificant in models without the lagged residuals.

ance from stage 1, supports the null hypothesis that telecommuting had no significant impact on airline PMT. This is not a surprising result. Many people would have argued a priori that no impact should be expected. And although we suggested in Section 2 that an impact on airline travel might occur, we believe such an impact is far more likely for telecommunications as a whole than for telecommuting alone. Nevertheless, the fact that telecommuting has a positive (albeit insignificant) coefficient in this model, compared to a negative coefficient in the model for VMT, offers suggestive (albeit insufficient) evidence that telecommuting may be contributing to an overall complementary relationship between telecommunications and air travel, while maintaining a net substitution effect on ground travel.

Table 14: Telecommuting Models for Residuals of Airline PMT Models (N = 11)

Model	Adjusted R^2	Explanatory variables		
		Constant	Lag 1 of the residuals of the corresponding model	Natural log of the number of telecommuters (in millions)
Airline PMT	0.144	-0.0345 (-0.610)	-0.588 (-1.831)	0.0308 (1.041)
Airline PMT per capita	0.154	-0.0334 (-0.535)	-0.608 (-1.940)	0.0169 (0.527)

Notes:
Each dependent variable comprises the residuals of the corresponding estimated time series model in Table 13.
The number in parentheses indicates the t-statistic for that coefficient. Critical t-values for $\alpha = 0.05$ and 0.1, with 8 degrees of freedom, are 2.306 and 1.860, respectively.

Table 15 translates the results of the stage 1 and stage 2 models into impacts of telecommuting on annual PMT, % change in annual VMT, change per telecommuter, and change per telecommuting occasion for 1998. Although mean changes are positive for both PMT and PMT per capita models, in each case both the 95% and 90% confidence intervals enclose the value zero, meaning that the null hypothesis of no change cannot be rejected. With 95% confidence, the preferred airplane PMT per capita model leads to a change in PMT that falls between a 4.0% decrease and a 6.4% increase, representing a decrease of 1,617 miles to an increase of 2,575 miles annually per telecommuter, respectively (with the midpoint representing an increase of 479 miles).

Table 15: Estimated Impact of Telecommuting on Airline PMT in 1998 (using the 95% and 90% confidence intervals for the estimated coefficient of telecommuting)

Model			Change in annual PMT (millions of miles)			% change in annual PMT			Change in annual PMT per telecommuter (miles)			Change in PMT per occasion (miles)		
			Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
Airline PMT														
	95%	50 occasions/year	-17,917	14,733	47,383	-2.82	2.32	7.46	-1,141	938	3,018	-22.8	18.8	60.4
		75 occasions/year										-15.2	12.5	40.2
	90%	50 occasions/year	-11,596	14,733	41,061	-1.82	2.32	6.46	-739	938	2,615	-14.8	18.8	52.3
		75 occasions/year										-9.8	12.5	34.9
Airline PMT per capita			(miles)											
	95%	50 occasions/year	-94	28	150	-3.99	1.18	6.36	-1,617	479	2,575	-32.3	9.6	51.5
		75 occasions/year										-21.6	6.4	34.3
	90%	50 occasions/year	-70	28	126	-2.99	1.18	5.36	-1,211	479	2,169	-24.2	9.6	43.4
		75 occasions/year										-16.1	6.4	28.9

Notes:
A negative sign indicates a reduction in airplane PMT, while a positive sign indicates an increase in airplane PMT.
Based on 50 and 75 annual average telecommuting occasions, the change in airplane PMT per occasion is calculated for each case.

5.4 Multivariate Analysis: Total Miles Traveled

As can be seen from Figure 1, the sum of ground VMT and airline PMT is dominated by ground VMT, which constitutes between 79 and 91% of total miles traveled across the time series. Thus, it is not surprising that the stage 1 models for total miles traveled strongly resemble the VMT-only models.

5.4.1 First Stage Total Miles Traveled Models (without Telecommuting)

Table 16 presents the best stage 1 models for total miles traveled absolutely and per capita, respectively. The best model for absolute total miles traveled has the same specification as the Alternative 3 VMT model in Table 9. The coefficient for population has a slightly better p-value here (0.088) than in the VMT model (0.136). It represents the best model for absolute total miles traveled for the same reasons as discussed in Section 5.2.1 with respect to the VMT model. The best model for total miles traveled per capita has the same specification as the (preferred) Alternative 5 model for VMT per capita shown in Table 9. Here, as there, the coefficient for CPI-transportation has a counterintuitive positive sign, but a net negative impact when considered jointly with the CPI-all variable. Here, as there, experimentation with variations on this specification did not yield a superior model.

Adjusted R^2s for these two models are 0.645 and 0.666, respectively, the latter being the highest adjusted R^2 obtained across all the final models presented here. For this reason, as well as the interpretability of the model and consistency with the model selected for VMT, we prefer the total miles per capita model. Its interpretation is identical to that of its VMT counterpart.

Table 16: Multivariate Time Series Models for Total Miles Traveled (N = 33)

Model	Adjusted R^2	Explanatory variables						
		Constant	GDP per capita	Gasoline price	Miles per gallon	CPI (all)	CPI (transportation)	Population
Total miles traveled	0.645	0.000230 (0.004)	0.326 (5.630)	-0.0273 (-2.231)	0.158 (1.965)	-0.425 (-1.802)		0.929 (1.770)
Total miles traveled per capita	0.666	0.132 (5.028)	0.395 (5.093)	-0.0601 (-2.962)	0.257 (2.404)	-1.516 (-3.496)	0.539 (2.245)	

Notes:
All dependent and explanatory variables are the standardized, first-order differenced (i.e. $X_t – X_{t-1}$) variables.
The number in parentheses indicates the t-statistic for that coefficient. The degrees of freedom are N-k where k is the number of parameters estimated. Critical t-values for α = 0.05 and 0.1, with 27 degrees of freedom, are 2.052 and 1.703, respectively.

5.4.2 Second Stage Total Miles Traveled Models: The Impact of Telecommuting

Table 17 presents the best stage 2 models for the two total miles traveled variables. In the first model, telecommuting is completely insignificant (p-value = 0.186) and the adjusted R^2 is quite low, only 0.095. The second model, for total miles per capita, is very similar to the stage 2 model for its VMT counterpart, with the addition of the lagged residuals variable for the same reasons as it was needed in the PMT models. As with the VMT per capita model, the telecommuting variable is significant (at the 0.1 level) and negative.

It might have been expected that the small but positive effect of telecommuting in the PMT per capita model would partly counteract the negative effect in the VMT per capita model, yielding an effect on total miles per capita that was smaller in magnitude (less negative) than for VMT per capita. Instead, the coefficient of telecommuting is slightly more negative here (-0.0535) than for the VMT per capita model (-0.0499). In view of the different specifications among the three models, and the fact that the telecommuting variable enters each model in a non-linear transformation, additivity of the effects will not be exact. In point of fact, the estimated coefficients for the two models are not significantly different. Given the insignificant coefficient of telecommuting in the PMT model, it is not surprising that the null hypothesis of equality between the telecommuting coefficients in the other two models could not be rejected. On the other hand, neither could one reject the null hypothesis that the true coefficient for the total model is in fact slightly smaller in magnitude than the true coefficient for the VMT-only model, as would be expected if the coefficient for the PMT model is in fact slightly positive.

Table 17: Telecommuting Models for Residuals of Total Miles Traveled Models (N = 11)

Model	Adjusted R^2	Explanatory variables		
		Constant	Lag 1 of the residuals of the corresponding model	Natural log of the number of telecommuters (in millions)
Total Miles Traveled	0.095	0.0497 (1.452)		-0.0250 (-1.432)
Total Miles Traveled per capita	0.252	0.109 (2.265)	-0.479 (-1.547)	-0.0535 (-2.254)

Notes:
Each dependent variable comprises the residuals of the corresponding estimated time series model in Table 16.
The number in parentheses indicates the t-statistic for that coefficient. Critical t-values for α = 0.05 and 0.1, with 8 (9) degrees of freedom, are 2.306 (2.262) and 1.860 (1.833), respectively.

Table 18 presents the estimated impact of telecommuting in 1998, in terms of absolute and percent changes in observed total miles traveled, as well as change per telecommuter and change per telecommuting occasion. Since the telecommuting coefficient in the preferred per capita model is significant at the 0.1 level but not the 0.05 level, the 90% confidence interval results do not enclose zero, whereas the 95% confidence interval results do. In other words, as with the VMT-only results, we can be 90% confident, but not 95% confident, that telecommuting significantly reduces total miles traveled. With 90% confidence, the true impact of telecommuting on total miles traveled falls between reductions constituting 0.45% and 4.69% of observed total miles traveled, whereas with 95% confidence, the true impact is somewhere between a 5.19% reduction and a 0.06% increase (the latter representing virtually no impact).

The midpoint total numbers of miles reduced per telecommuting occasion are even more extreme for this model than for the VMT-only model (Tables 11 and 12). Thus, as for that model, based on external considerations the true effects are likely to lie closer to the upper bounds of the two confidence intervals, e.g. 11.7 – 17.5 miles reduced per occasion for the 90% confidence interval.

Table 18: Estimated Impact of Telecommuting on Total Miles Traveled in 1998 (using the 95% and 90% confidence intervals for the estimated coefficient of telecommuting)

Model		Change in annual total (millions of miles)			% change in annual total			Change in total per telecommuter (miles)			Change in total per occasion (miles)		
		Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
Total Miles Traveled													
95%	50 occasions/year	-116,011	-44,965	26,082	-3.79	-1.47	0.85	-7,389	-2,864	1,661	-147.8	-57.3	33.2
	75 occasions/year										-98.5	-38.2	22.1
90%	50 occasions/year	-102,537	-44,965	12,608	-3.35	-1.47	0.41	-6,531	-2,864	803	-130.6	-57.3	16.1
	75 occasions/year										-87.1	-38.2	10.7
Total Miles Traveled per capita			(miles)										
95%	50 occasions/year	-589	-291	7	-5.19	-2.57	0.06	-10,138	-5,011	116	-202.8	-100.2	2.3
	75 occasions/year										-135.2	-66.8	1.5
90%	50 occasions/year	-531	-291	-51	-4.69	-2.57	-0.45	-9,145	-5,011	-877	-182.9	-100.2	-17.5
	75 occasions/year										-121.9	-66.8	-11.7

Notes:
A negative sign indicates a reduction in total miles traveled, while a positive sign indicates an increase in total miles traveled.
Based on 50 and 75 annual average telecommuting occasions, the change in total miles traveled per occasion is calculated for each case.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Overview of Results

This study estimates the impact of home-based telecommuting on personal transportation through a multivariate time series analysis of aggregate nationwide data spanning 1966-1999 for all variables except telecommuting, and 1988-1998 for telecommuting. Three dependent variables were modeled, in direct and per-capita forms: ground vehicle-miles traveled (VMT), airline passenger-miles traveled (PMT), and the sum of those two variables, loosely referred to as "total miles traveled". The analysis was conducted in two stages. In the first stage (after ensuring that all series were stationary through first-differencing and log transformations), each dependent variable (1966-1999) was modeled as a function of conventional variables representing economic activity (e.g. GDP, employment, disposable income), the cost of transportation (e.g. gasoline price, fuel efficiency, CPI for transportation), transportation supply (lane-miles of roadways), and demographics (e.g. population, household size, licensed drivers, number of personal vehicles). A total of 15 explanatory variables were allowed to enter the first-stage models. In the second stage, the residuals of the first stage (1988-1998) were modeled as a function of the number of telecommuters.

The study necessarily relied on secondary data sources, but some of the issues associated with the data used were discussed in Section 4. The critical telecommuting variable in particular has a number of concerns associated with its measurement, and for reasons presented in Section 4.3, it is likely that the data used here overestimate the true number of telecommuters. Although no better data on telecommuting are available, these concerns should be kept in mind in interpreting the empirical results.

For convenience, Tables 19 and 20 summarize the coefficients and telecommuting effects (in 1998) for the preferred models of each of the three dependent variables analyzed in this study. We briefly discuss the key results for each variable in turn.

Ground VMT per capita: The first stage model has an adjusted R^2 of 0.65. The five significant variables (besides the constant term) represent economic activity and the cost of transportation, with GDP per capita and miles per gallon having the expected positive signs, and gasoline price and the combined effect of CPI-all and CPI-transportation having the expected negative signs. The second stage model has an adjusted R^2 of 0.27, and the coefficient for number of telecommuters is significant and negative, suggesting that telecommuting does measurably reduce VMT.

When the amount of that reduction is quantified, however, concerns regarding its plausibility emerge. Using the estimated coefficient of telecommuting directly, the estimated impact on VMT in 1998 translates to a reduction of 66 miles per telecommuting occasion on the assumption of 50 occasions per year (about once a week), and 44 miles per occasion at an assumed 75 occasions per year (about 1.5 times a week). Even the lower number of 44 miles seems unrealistically high compared to benchmark data on average commute lengths and average daily VMT. Thus, we present the VMT reductions estimated by the 95% and 90% confidence intervals on the coefficient of telecommuting, and consider the true mean impact more likely to lie in the upper halves of those intervals. The 95% confidence interval on the coefficient encloses the value zero, meaning that with that standard, we cannot reject the null hypothesis that telecommuting has no impact on VMT. On the other hand, the 90% confidence interval does not include zero.

Table 19: Summary of Preferred Multivariate Time Series Models

Model	VMT per capita	Airline PMT per capita	Total miles traveled per capita
1st stage model			
No. of observations	33	32	33
Adjusted R^2	0.649	0.552	0.666
Constant	0.153 (4.866)	0.0655 (4.102)	0.132 (5.028)
GDP per capita	0.366 (3.936)	0.285 (2.449)	0.395 (5.093)
Gasoline price	-0.0936 (-3.847)		-0.0601 (-2.962)
Gasoline price (1st order lag)		-0.0827 (-3.882)	
Miles per gallon	0.352 (2.737)		0.257 (2.404)
CPI (all)	-2.076 (-3.990)		-1.516 (-3.496)
CPI (transportation)	0.834 (2.895)		0.539 (2.245)
2nd stage model			
No. of observations	11	11	11
Adjusted R^2	0.273	0.154	0.252
Constant	0.102 (2.284)	-0.0334 (-0.535)	0.109 (2.265)
The residuals of the corresponding model (1st order lag)		-0.608 (-1.940)	-0.479 (-1.547)
Natural log of the number of telecommuters (in millions)	-0.0499 (-2.183)	0.0169 (0.527)	-0.0535 (-2.254)

Notes:
All dependent and explanatory variables are the standardized, first-order differenced (i.e. $X_t - X_{t-1}$) variables.
The number in parentheses indicates the t-statistic for that coefficient. The degrees of freedom are N-k where k is the number of parameters estimated, and hence ranges from 8 to 29 for these models. Critical t-values for $\alpha = 0.05$ and 0.1, with 8 (29) degrees of freedom, are 2.306 (2.045) and 1.860 (1.699), respectively.

Table 20: Summary of Estimated Impact of Telecommuting on Miles Traveled in 1998 (using the 95% and 90% confidence intervals for the estimated coefficient of telecommuting)

Model		Change in annual distance per capita (miles)			% change in annual distance per capita			Change in annual distance per telecommuter (miles)			Change in distance per occasion (miles)		
		Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound	Lower bound	Mean	Upper bound
VMT per capita													
95%	50 occasions/year	-387	-190	7	-4.31	-2.12	0.08	-6,667	-3,274	119	-133.3	-65.5	2.4
	75 occasions/year										-88.9	-43.6	1.6
90%	50 occasions/year	-350	-190	-30	-3.89	-2.12	-0.34	-6,023	-3,274	-524	-120.5	-65.5	-10.5
	75 occasions/year										-80.3	-43.6	-7.0
Airplane PMT per capita													
95%	50 occasions/year	-94	28	150	-3.99	1.18	6.36	-1,617	479	2,575	-32.3	9.6	51.5
	75 occasions/year										-21.6	6.4	34.3
90%	50 occasions/year	-70	28	126	-2.99	1.18	5.36	-1,211	479	2,169	-24.2	9.6	43.4
	75 occasions/year										-16.1	6.4	28.9
Total Miles Traveled per capita													
95%	50 occasions/year	-589	-291	7	-5.19	-2.57	0.06	-10,138	-5,011	116	-202.8	-100.2	2.3
	75 occasions/year										-135.2	-66.8	1.5
90%	50 occasions/year	-531	-291	-51	-4.69	-2.57	-0.45	-9,145	-5,011	-877	-182.9	-100.2	-17.5
	75 occasions/year										-121.9	-66.8	-11.7

Notes:
A negative sign indicates a reduction in miles traveled, while a positive sign indicates an increase in miles traveled.
Based on 50 and 75 annual average telecommuting occasions, the change in miles traveled per occasion is calculated for each case.

Taken together, these results can be simply summarized as follows:

- Assuming the specified models are the correct ones, we can be 90% confident that telecommuting reduces VMT (by an amount as little as 0.34% of the observed VMT in 1998), but not 95% confident.
- The amount of that reduction is most likely small, falling somewhere between a 2% reduction in VMT and essentially no change in VMT.

It is interesting to compare these results to a previous study estimating the aggregate impact of telecommuting on VMT (Mokhtarian, 1998). That study analyzed "base case" and "future" scenarios. For the base case scenario, the level of telecommuting was estimated at about 6% of the workforce, using 1992 empirical data on the adoption of telecommuting among employees of the City of San Diego, California. This estimated level of telecommuting is consistent both with estimates independently obtained from a statewide travel diary survey conducted in California in 1991, and the nationwide number of telecommuters obtained by the LINK Resources market research firm in 1992 (see Table 2 in Section 4.3.1). For the future scenario (date unspecified), the level of telecommuting was estimated at 11.4% of the workforce, based on assumptions about the increasing proportion of the workforce able to telecommute. This assumed level of telecommuting is roughly consistent with the 1998 estimate (15.7 million, 12% of the workforce) made by the CyberDialogue market research firm and used in this study.

Therefore, using the previous study's future case scenario assumptions of (1) a 27-mile average round trip commute distance for telecommuters, (2) a factor of 0.76 for the proportion of commute miles that are drive-alone, and (3) an average telecommuting frequency of 1.2 days a week (say 60 occasions a year), we obtain an estimate of (27 x 0.76) VMT saved/telecommuter/occasion x 15.7 million telecommuters x 60 occasions/ year = 19,329.84 million vehicle-miles/year saved due to telecommuting. This constitutes 0.79% of the 2,428,135 million VMT measured in 1998. This effect is certainly congruent with the results obtained in the present study (falling in the upper half of the range obtained from the 90% confidence interval on the effect of telecommuting). However, that informal calculation only accounts for travel savings due to telecommuting; it does not include any increases in travel due to factors such as non-work trip generation, residential relocation, and the realization of induced or latent demand. In contrast, the models estimated in the current study *do* account for such effects, because the observed VMT that constitutes the dependent variable in the model will include any such effects. The limited empirical evidence available on this question suggests that those travel-increasing effects are small relative to the savings, but whatever their magnitudes, they will act to reduce the transportation benefit of telecommuting. Thus, in our opinion, a reduction of 0.79% of VMT represents a reasonable upper bound on the effect of telecommuting on VMT in 1998, taking both internal statistical evidence and external reality checks into consideration.

On the other hand, it should again be pointed out that if the estimate of 15.7 million telecommuters is high, as some evidence suggests, then the impact on VMT will be accordingly lower. Another caveat is that when we are dealing with effects this small (perhaps only fractions of a percent), the results are inevitably sensitive to model specifications. As Table 11 shows, the estimated impact of telecommuting could be as high as 5% of VMT under at least one specification tested in the study, albeit one that we consider inferior to the final one selected. In general, the worse the first-stage model is (i.e. the less variation in VMT that is explained by variables other than telecommuting), the more powerful the effect of telecommuting will appear to be. Conversely, if we were able to improve the specification of the best first-stage model beyond the current adjusted R^2 of 0.65, there would be less residual variation for telecommuting to explain and its estimated effect could become weaker. In view of these issues and the endogeneity bias concerns discussed in the Introduction, it would be dangerous to place too much emphasis on the specific quantitative results obtained here.

Airline PMT per capita: The preferred first-stage model has an adjusted R^2 of 0.55, and contains just two variables (plus the constant): GDP per capita, and gasoline price (lagged one year). In the second-stage model, telecommuting has a positive but insignificant coefficient. Thus, the safest (and plausible) conclusion is that telecommuting has no impact on airline travel, although the potential indication of a complementarity effect should be monitored in the future as additional data become available.

Total miles traveled per capita: Since ground VMT constitutes 79-91% of total miles traveled, the first-stage model for the latter variable closely resembles the one for the former variable, with a slightly higher adjusted R^2 of 0.67, and the same variables being significant. In the second-stage model, the telecommuting coefficient is also similar to its counterpart in the VMT model. As in that model, we can be 90%, but not 95%, confident that telecommuting reduced total miles traveled in 1998.

It is also of interest to comment on two variables that were *not* found to be significant in the final models: lane-miles and number of vehicles. As mentioned in Section 2.1, an extensive literature examines the impact of increasing network capacity on travel, by modeling VMT as a function of lane-miles as well as economic and other variables. The fact that the lane-miles variable is inevitably found to be significant in those induced demand studies but is not significant here, is intriguing. Its absence here is presumably not due to correlations with included variables, since the pairwise correlations and factor analysis shown in Tables 4 and 5 of Sections 4.4 and 4.5 demonstrate that the lane-miles variable has very little variation in common with the other explanatory variables (in their first-differenced forms, as used in our models).

One speculation is that if the time series in the induced demand studies were not made stationary before building the models, the significance of lane-miles could be due to third-party correlation with time: as the pairwise correlations in Table 3 show, in raw form, lane-miles *is* highly correlated with the other variables in this study, including VMT. Another difference with some of the induced demand studies is that we included lane-miles for all facility types, whereas some studies restricted their analysis only to higher-level facility types. As DeCorla-Souza (2000) points out, by not including lower-level facilities such as minor arterials in the analysis, shifts in traffic from minor facilities to the major ones under study would erroneously be counted as induced demand. Further, increases in lane-miles over time can be due to the reclassification of minor facilities into major ones (or, when the unit of observation is a metropolitan area, through the incorporation of additional land into the officially-designated metro area), rather than through true capacity increases. The VMT on these reclassified facilities would augment total VMT accordingly, but that would not represent the same causal mechanisms as generation of completely new traffic (whether induced or "natural").

The second explanatory variable that is intriguing by its absence is number of vehicles. Conventional wisdom holds that vehicles themselves tend to induce vehicle travel, but this is not borne out by our results. Again, inspection of Tables 4 and 5 suggests that the absence of this variable does not appear to be due to overly high correlations with included variables, but there could still be a subtle network of connections through correlations among number of vehicles per capita, employment, disposable income, and GDP. Based on the present results, it seems that if employment and disposable income are indirectly accounted for through the presence of GDP in the model, there is no residual effect of number of vehicles on VMT. However, here is a case where a more elaborate system of structural equations may be able to identify an effect that is not apparent in our single-equation model.

6.2 Recommendations

Given that telecommuting appears to have a statistically significant – albeit modest in magnitude – effect on reducing travel, several public policy recommendations suggest themselves.

First and perhaps foremost, better data is of paramount importance to a more precise determination of the true impact of telecommuting on VMT. As this study demonstrates, a great deal of uncertainty surrounds estimates of the number of telecommuters and frequency of telecommuting, and a wide range of answers to the question of "what impact on travel?" can be obtained. Telecommuting appears to be an important enough trend to justify the cost and effort required to collect reliable data with respect to its adoption and frequency, on an annual basis.

In view of its apparently beneficial transportation-related impacts, public agencies could consider several strategies for increasing the adoption of telecommuting. One such strategy is simply to collect and widely disseminate case-study information on telecommuting successes. Where costs and benefits can be quantified, the business case for telecommuting can be compelling. Case studies are more important in the many situations in which the costs of telecommuting may be evident and quantifiable, but the benefits may be less evident and less easy to quantify. Individual organizations are likely to be receptive to evidence showing that major competitors in the same industry have successfully adopted telecommuting and consider it a net benefit. In at least one study (Illegems, *et al*., 2001, p. 290), human resources managers "viewed the widespread dissemination of information on 'best teleworking practices' in large and well-known companies as the most efficient way to obtain an enhanced implementation of teleworking" and as "the most effective policy tool to promote teleworking".

Public agencies have also occasionally considered (and some have implemented) tax credits for organizations who adopt telecommuting. However, the modest incentives that are usually involved in such proposals may not be sufficient in their own right to overcome the managerial resistance that often exists. Further, enforcement must be a concern, with possibly a high potential for false claims on the part of organizations or their employees. Even if reported telecommuting is genuine, to judge the cost-effectiveness of this policy it should be determined to what extent the reported telecommuting was in fact stimulated by the tax incentive, rather than something that would have occurred anyway.

Finally, one or more variables relating to the cost of transportation was significant in every model presented here, with a negative impact on travel. Thus, it stands to reason that policies that increase the cost of travel – congestion pricing, fuel taxes – will reduce the amount of travel, and by extension will make telecommuting more attractive. Although in this case more telecommuting is arguably just a desirable by-product of a policy oriented toward reducing travel directly (rather than a direct object of the policy itself), there may also be some additional transportation benefits accruing from the adoption of telecommuting itself. For example, some studies have found that telecommuting not only reduced commute travel, but non-work travel as well, and not only of telecommuters but also of their household members (Mokhtarian, *et al*., 1995).

The encouraging transportation-related results obtained in this study, together with the other potential public and private benefits of telecommuting, certainly support further commitment to increasing its adoption, and further refinement of our knowledge of its impacts.

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