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REDUCE VEHICLE-MILES TRAVELED?
AN AGGREGATE TIME SERIES ANALYSIS FOR THE U.S.

by

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Abstract

This study examines the impact of telecommuting on passenger vehicle-miles traveled (VMT) through a multivariate time series analysis of aggregate nationwide data spanning 1966-1999 for all variables except telecommuting, and 1988-1998 for telecommuting. The analysis was conducted in two stages. In the first stage, VMT (1966-1999) was modeled as a function of conventional variables representing economic activity, transportation price, transportation supply and socio-demographics. In the second stage, the residuals of the first stage (1988-1998) were modeled as a function of the number of telecommuters. We also assessed the change in annual VMT per telecommuter as well as VMT per telecommuting occasion, for 1998. The models suggest that telecommuting reduces VMT, with 94% confidence. Together with independent external evidence, the results suggest a reduction in annual VMT on the order of 0.8% or less. Even with impacts that small, when informally compared to similar reductions in VMT due to public transit ridership, telecommuting appears to be far more cost-effective in terms of public sector expenditures.

Keywords: aggregate analysis, telecommuting, teleworking, time series analysis, vehicle-miles traveled (VMT) modeling/forecasting

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INTRODUCTION

Teleworking is defined for this study 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. 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.

In general, telecommuting *per se* appears to have considerable popular appeal, although a number of barriers prevent it from achieving the penetration that might be expected from consideration of its potential benefits alone. Nevertheless, perhaps facilitated by several high-profile public-sector demonstration projects in the late 1980s and early 1990s (e.g. Kitamura, *et al.*, 1990; 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 best data available (see Mokhtarian, *et al.*, 2004 for an in-depth critique of various estimates of the amount of telecommuting in the U.S., some of which are shown in Figure 2, discusssed later; the statistics presented here are based on the "Market Research Firms" series of that figure) indicate that about 12% of the workforce telecommuted at least once a month in 1998, with an average annual growth rate of 20% since 1988. However, some evidence also suggests that the amount of telecommuting in the U. S. may be leveling off, reaching a natural dynamic equilibrium in which new adopters are approximately balanced by dropouts (see Mokhtarian, *et al.*, 2004 and Varma, *et al.*, 1998).

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*., 1991). Despite the now-common inclusion of telecommuting in public policy instruments directed toward reducing travel (from regional transportation plans and air quality regulations, to state legislation and Federal executive orders, laws, and programs), a number of questions about its transportation impacts remain without clear answers to date. On one hand, many small-scale empirical studies (e.g. Hamer, *et al*., 1991; Henderson, *et al.*, 1996; Mokhtarian and Varma, 1998; Mokhtarian, *et al*., 1995; Nilles, 1988; Pendyala, *et al*., 1991) 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. On the other hand, an important 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 *empirical* study of the impact of teleworking on transportation has not previously been conducted, although several scenario-based projection studies have been produced (see, e.g., USDOE, 1994).

The purpose of this study is to estimate the impact of telecommuting on vehicle-miles traveled (VMT) of personal transportation through a multivariate time series analysis, using aggregate nationwide data. Therefore, in this study, we focus on a single direction of causality and a subset of all telecommunications activity, to explore the impact of telecommuting on VMT. This is a limitation that must be kept in mind in interpreting the results. In fact, 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. However, this limitation is common to nearly all the numerous published studies that model aggregate VMT (e.g. Springer and Resek, 1981; Gately, 1990; Greene, 1992; Schimek, 1996). With that caveat in mind, in any case, 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, it is desirable to see whether the substitution effect observed in the disaggregate studies can be replicated, that is, whether, after filtering out other forces expected to influence aggregate VMT, telecommuting has an effect that can be detected.

In the following sections, we describe the data used for this study, and the time series analysis methodology we employed. Then, the modeling results are presented: several candidate first-stage models containing all explanatory variables except telecommuting, and the corresponding second-stage models containing telecommuting to see if it adds significant explanatory power. Finally, conclusions and policy recommendations are discussed.

DATA DESCRIPTION

Aggregate time series data is used for this study of telecommuting on personal transportation over time. Of necessity due to time and resource constraints, we rely on secondary sources for the data, usually collected by trade or private sector organizations, government agencies, or other public agencies. Figure 1 presents the time trends for the dependent variables as well as key explanatory variables. It can be seen that most of the explanatory variables exhibit a rising trend similar to that of VMT (however, see the later discussion regarding the need for stationarity in each series), while the most notable exception, gasoline prices, may be useful in explaining fluctuation of VMT around a deterministic upward trend.

[Figure 1 goes about here]

The Dependent Variable

The primary dependent variable of the current study is *vehicle-miles traveled* or VMT: annual passenger vehicle-miles traveled (i.e. miles traveled by light-duty autos and light-duty trucks in the US in a given year). Specifically, total VMT is annually reported by each state to the Federal Highway Administration (FHWA). 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.

The Explanatory Variables

We considered several key types of influences on VMT, such as economic factors, transportation price and supply factors, and socio-demographic factors, in addition to telecommuting, and efforts were made to obtain data on each key type. The explanatory variables used in this study include those appearing most often in models of VMT identified in our review of the literature. For example, a number of studies (e.g. Springer and Resek, 1981; Gately, 1990; Greene, 1992; Schimek, 1996) have modeled VMT as a function of economic indicators (GNP or GDP), gasoline price and fuel efficiency using aggregate time series data. Ultimately, a total of 15 explanatory variables besides telecommuting were selected for initial model specification:

- *Economic activity:* real gross domestic product (GDP), real disposable income, employment, unemployment rate, federal interest rate;
- *Transportation price:* real gasoline price, fuel efficiency (miles per gallon), consumer price index (CPI) of all urban consumers for all items[1], CPI of all urban consumers for transportation;
- *Transportation supply:* lane-miles;
- *Socio-demographics:* population, household size, licensed drivers, number of personal vehicles, proportion of the population living in suburban areas.

Many other variables were considered, but had to be excluded either because of high correlations with other variables, sometimes coupled with lack of significant impact in preliminary testing (e.g. the CPIs for personal vehicles and public transportation, the percentage of licensed drivers who were female), or because adequate measurements of them were not available for the entire period of interest (e.g. population and employment densities in metropolitan areas).

[1] The Consumer Price Index (CPI) is a measure of the overall level of prices (paid by urban consumers) that indicates the cost of a fixed market basket of consumer goods and services relative to the cost of the same basket in a base year (Mankiw, 2003). The Bureau of Labor Statistics publishes the consumer price indices for all items and specific types of goods every month.

All data on vehicle-miles traveled (VMT), number of vehicles, and fuel efficiency and consumption 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 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 CPI, 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, the first-stage models analyzed here are based on 34 observations, from 1966 to 1999.

Factor analysis was conducted on these 15 (differenced) explanatory variables, to reduce the problems caused by multicollinearity. Factor analysis develops a smaller number of essentially uncorrelated composite measures, where each composite measure is some linear combination of the correlated variables. Four factors, similar to the key types of explanatory variables outlined above, were identified, accounting for 70% of the total variance in all the variables. Despite the intuitive nature of these factors, however, there is no guarantee that they will improve the models. They will do so if in fact it is really the latent variables (composite factors) that are the true influences on VMT, and the constituent observed variables do a good job of measuring the latent variables. On the other hand, if the true influences on VMT are better captured by the individual observed variables themselves, then the models will generally be better by letting the coefficients of the individual variables each be freely estimated (by entering them directly into the models), than by only allowing them to enter the model through the linear combination comprising the factor score, and thereby (in effect) constraining their coefficients to be proportional to the coefficient of the factor.

In our case, 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.

The Telecommuting Variable

A number of organizations have produced estimates of the amount of telecommuting or home-based work in the US from time to time, primarily in terms of the number of telecommuters. Four different sources of published data on the number of home-based workers in the US were identified for this study. Figure 2 presents the data on number of telecommuters provided by 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.

[Figure 2 goes about here]

Some large discrepancies between sources can be observed in the figure. They are probably mainly caused by differences in definitions of telecommuting, by sampling error, and by errors in weighting the sample to achieve population representativeness. 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 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.

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 of market research data 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 presented in greater detail by Mokhtarian, *et al*. (2004), it is likely that the data used here overestimate the true number of telecommuters.

We will assess the change in annual VMT per telecommuter for the latest year available (1998), 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 relatively stable average frequencies of telecommuting over time found in the literature (see, e.g., Mokhtarian, 1998), 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).

METHODOLOGY

In this study, we take the widely-practiced Box-Jenkins (1976) approach to 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. The identification is suggested by patterns either in the raw series itself, or in the residuals from a previously-estimated model. At the initial identification stage, autocorrelation of the raw series is expected, and can be modeled explicitly through either a univariate or multivariate specification. Simultaneous *estimation* of the parameters of the identified model is done via least-squares, maximum likelihood, or some other approach using one of a number of special-purpose routines devoted to time series analysis (such as modules within SAS, Limdep, or EViews). Finally, the residuals from the estimated model are *diagnosed* to see if there are any patterns left that indicate an incorrect or incomplete specification. At this stage, neither autocorrelation nor other time-dependent trends in the residuals should occur; the desirable pattern is one of white noise, or purely random variation. The Durbin-Watson test is one common approach to checking for a residual pattern of white noise. If this pattern is not achieved, the three-step process is repeated.

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). Modeling VMT directly as a function of telecommuting together with the other variables, would mean the loss of many data points and hence degrees of freedom, making the resulting model statistically unreliable. Further, 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 can be explained by telecommuting. Thus, we adopted a two-stage approach for this study. First, we modeled VMT as a function of all variables other than telecommuting, for the full 34-year series. Next, we computed the unexplained residual of VMT from that model. Finally, using only the 11 observations corresponding to the years 1988-1998, we modeled that residual time series as a function of telecommuting.

MODEL ESTIMATION

This section presents the results of the two-stage models described in the previous section. Prior to estimating the first-stage models, we standardized each variable (with one exception discussed below) to control for drastic differences in scale.

In the classic Box-Jenkins methodology, the first step in analyzing a series 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 station-arity. 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 the true relationship between two series can be ascertained.

In the current study, each time series variable was non-stationary in its raw form, but in every case except one, first-order differencing of the series achieved stationarity. In the case of the telecommuting variable, two forms of the series, a simple natural log and a first-order difference, were considered to achieve stationarity. Neither the Augmented Dickey-Fuller unit root test nor the Durbin-Watson test statistics for the residuals of the second-stage estimation provided a strong basis for choosing between the two forms. Based on visual inspection of the correlogram, the first-order difference form was more stationary than the natural log one. However, differencing the telecommuting series would have reduced the already small number of observations available for estimation from 11 to 10. We considered the log transform preferable to preserve the additional degree of freedom, given that the Durbin-Watson test statistic (of 2.17, see Table 2) for this transformation was satisfactory. However, using the log transform for the telecommuters variable meant that it could not be standardized before transformation, since the log transform is undefined for negative numbers.

We extensively explored including various lagged explanatory variables in the models, on the basis of both the univariate models for each variable and the cross-correlation function of each explanatory variable with the dependent variable[2], but for the most part lagged terms were not significant in the final models presented here. The econometric software package EViews

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[2] 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.

4.0 (Quantitative Micro Software, 2000) was used to estimate the models in view of its user-friendliness and graphical interface.

First Stage 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). 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 Tables 1 and 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 1 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)[3]. Durbin-Watson statistics for the models ranging from 1.57 to 1.92 show that there is no autocorrelation between residuals, since the statistics are greater than the upper bounds for the critical values, which vary by the sample size and number of regressors (Savin and White, 1977). Because all variables are standardized, the magnitudes of the estimated coefficients can be

[3] 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. Given the high pairwise correlations of our undifferenced data (shown in Table 3 of Choo, *et al*., 2001), we obtained similarly large R^2s for models based on the raw data.

viewed as direct indicators of the relative impact of the associated explanatory variable on the dependent variable.

[Table 1 goes about here]

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; 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 these 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.

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[4]. 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[5]. 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. Conlisk, 1971; Kennedy, 1998) suggest that it is appropriate to retain two variables even when they are highly correlated

[4] Although the dependent variables are different (VMT versus VMT per capita), they represent two alternative approaches to measuring the same conceptual construct (amount of passenger vehicle travel), and hence it is legitimate to inquire which of those two alternatives can be modeled more effectively with the available data. Assuming best models are identified in each case, a comparison of R^2s simply indicates that a greater proportion of variance in the dependent variable is explained in one case than in the other, i.e. that one form of the construct of interest can be modeled more effectively than the other.

[5] 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 resulted in Alternative 1 of the VMT per capita group.

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.

Second Stage VMT Models (the Impact of Telecommuting)

Table 2 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. Similar to the first stage models, Durbin-Watson statistics (1.70 - 2.36) for the models indicate that there is no autocorrelation between residuals. That is, white noise is achieved by the residuals for each model. 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.

[Table 2 goes about here]

As indicated in the previous section, 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 2, 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-value of 0.057 (and the expected negative sign, meaning that increases in the number of telecommuters result in decreased per-capita VMT).

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 (Ziliak and McCloskey, 2003). 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 3 and 4 for 1998, the last year in the time series on the number of telecommuters. Table 3 is based on the 95% confidence interval for the telecommuting coefficient, while Table 4 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.

[Tables 3 and 4 go about here]

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[6]. 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). Based on the literature, we are reasonably confident that these two assumptions 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 3, we note that the estimated mean percent changes in VMT are all reductions (as the uniformly negative coefficient estimates guarantee). The midpoint 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. To put these estimated impacts into context, it is of interest to compare them to those of public transportation. If it is assumed that every passenger-mile on public transportation would otherwise have been a passenger vehicle-mile in a light-duty auto or truck[7], the 44,128 million transit PMT in the US in

[6] 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.

[7] If one transit passenger-mile equated to one *person*-mile traveled by auto or truck, it would translate to only 0.63 *vehicle*-miles traveled in view of an average vehicle occupancy of 1.59 (obtained by dividing the 1998 auto/truck PMT of 3,855,696 million by the corresponding VMT of 2,428,135 million). This would change the impact of transit on VMT to 1.1%, making telecommuting look even stronger by comparison. On the other hand, some studies (Holtzclaw, undated) have argued that the average one-mile trip on transit replaces a trip of anywhere from 1.4 to 9 vehicle-miles in length, due to concomitant changes in destinations, routes, and overall mode mix. However, since these studies are based on disaggregate cross-sectional data mostly involving rail transit, a number of questions remain. Given the counteracting directions of the two effects mentioned here (one deflating the impact of transit on

1998 would have increased the 2,428,135 million VMT by 1.8% (see Tables 1-32 and 1-34 at http://www.bts.gov/publications/national_transportation_statistics/2003/index.html, accessed July 11, 2004). Thus, taken at face value, the midpoint estimated impact of telecommuting on VMT is comparable to or even greater than that of all the public transit ridership in the US put together! Since this implication seems dubious, 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 3 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. Although by construction the midpoint of the interval is the highest-probability fit to the data, in consideration of random sampling variation 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 3 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:

VMT, the other inflating it), for the purposes of the present discussion we simply assume a one-to-one relationship between transit PMT and passenger VMT.

- Based on the 1995 Nationwide Personal Transportation Survey (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-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, 1999). 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 again 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 4 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.

SUMMARY AND DISCUSSION 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. Vehicle-miles traveled (VMT) was modeled in direct and per-capita forms. 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, all of which have measurement issues. The critical telecommuting variable in particular has a number of concerns associated with its measurement, and 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.

The preferred 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 corresponding 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 suggest that other evidence on average commute lengths and disaggregate VMT savings per telecommuting occasion supports the true mean impact lying 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 (the p-value for the telecommuting coefficient is 0.057, meaning 94% confidence that there is an effect).

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.
- Taking independent external evidence into account, 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 of interest 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. 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 Cyber Dialogue 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 (27×0.76) VMT saved/telecommuter/occasion $\times$ 15.7 million telecommuters $\times$ 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. In the Model Estimation section we noted that public transportation accounted for travel roughly equivalent to 1.8% of VMT in 1998. Here we can comment that even if telecommuting "only" accounts for 0.8% of VMT, it still looks very cost-effective by comparison, when one considers that in 1998, federal, state, and local government expenditures on public transit totaled around $28 trillion (see Table 3-29a of http://www.bts.gov/publications/national_transportation_statistics/2003/index.html, accessed July 11, 2004), compared to, at most, tens of millions of dollars on telecommuting (personal communications with Ms. Kathy King of the State of Oregon and Dr. Wendell Joice of the US General Services Administration, both administrators of governmental telecommuting policies, July 13 and 15, respectively, 2004). This is not even counting the comparative sunk costs of the requisite infrastructures, on which public transit even further outstrips telecommuting.

If we must rely on external evidence to point to the "right" answer in this study, it is understandable to wonder (as one referee did) whether it was worth doing the time series modeling in the first place. We suggest that this investigation provides a good example of multiple techniques corroborating and refining each other to result in an outcome that is more reliable than either approach could have yielded alone. The value added by the external "reality check" conducted to refine our estimate of the magnitude of the impact of telecommuting is clear. What value is added by the time series analysis reported here? The estimate produced by the previous study could perhaps best be characterized as "informed speculation", based on an ad hoc synthesis of findings from a number of small disaggregate studies, among other sources. The present study, by contrast, represents a systematic, rigorous statistical analysis of aggregate data (for the first time, from this perspective). It is only such an analysis, not the more informal, speculative one of the previous study, that allows us to empirically demonstrate, within the limits of data quality and the confidence constraints of sampling error, that telecommuting does in fact have a detectable impact on VMT in the aggregate.

On the other hand, in addition to the measurement uncertainty for the number of telecommuters, VMT, and the other variables, and the ever-present possibility of a Type I error (falsely rejecting the null hypothesis of no impact), 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 specification. As Table 3 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 unwise to place too much emphasis on the specific quantitative results obtained here.

It is also of interest to comment on two variables that were *not* found to be significant in the final model: lane-miles and number of vehicles. An extensive literature (e.g., Noland, 2001) 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 demonstrated 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 showed, 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 pairwise correlations 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.

POLICY RECOMMENDATIONS

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

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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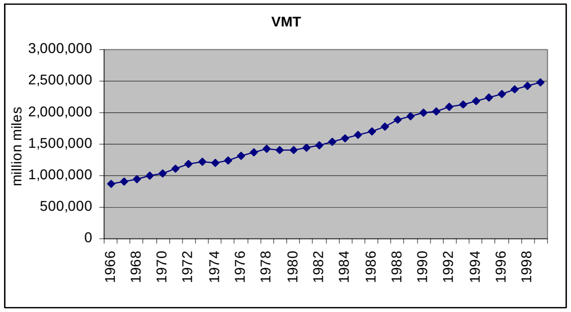
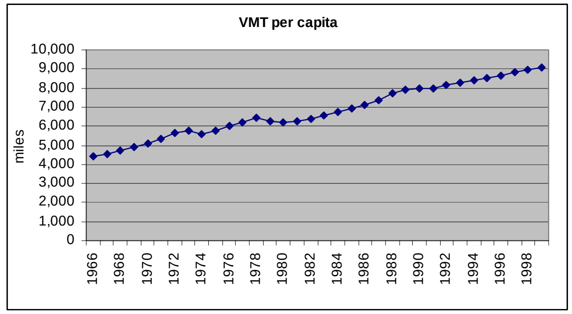
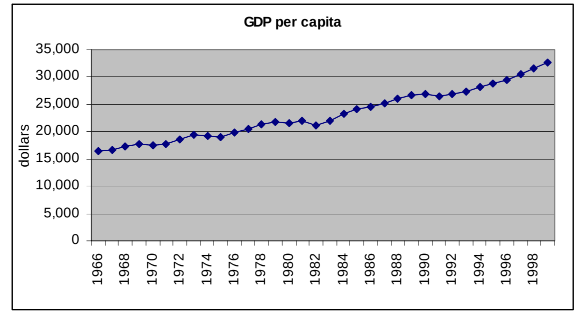
LIST OF TABLES AND FIGURES



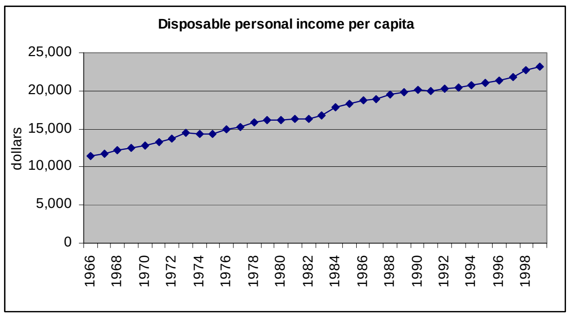
VMT (million miles, min: 868,894, max: 2,480,975)



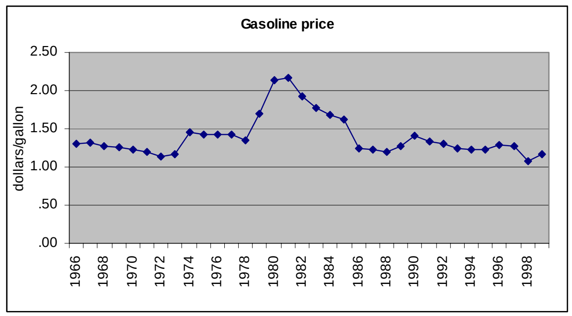
VMT per capita (miles, min: 4,421, max: 9,098)



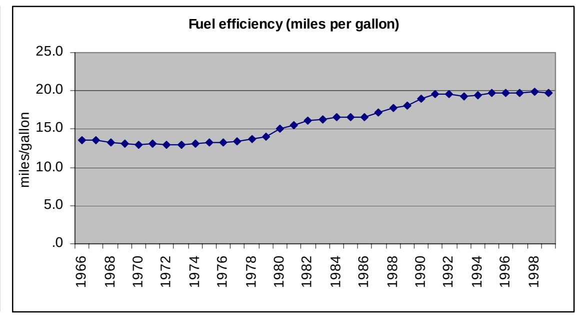
GDP per capita ($, min: 16,420, max: 32,549)



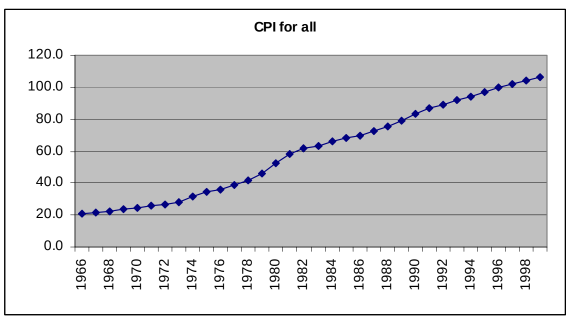
DPI per capita ($, min: 11,419, max: 23,217)



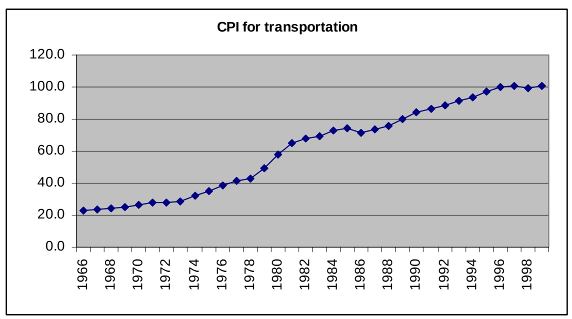
Gasoline price ($/gallon, min: 1.08, max: 2.17)



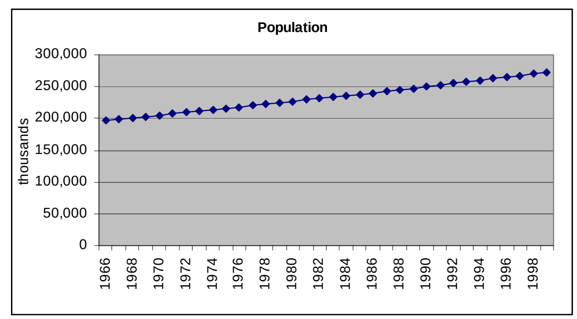
MPG (miles/gallon, min: 12.9, max: 19.8)



CPI for all (1996=100, min: 20.7, max: 106.2)

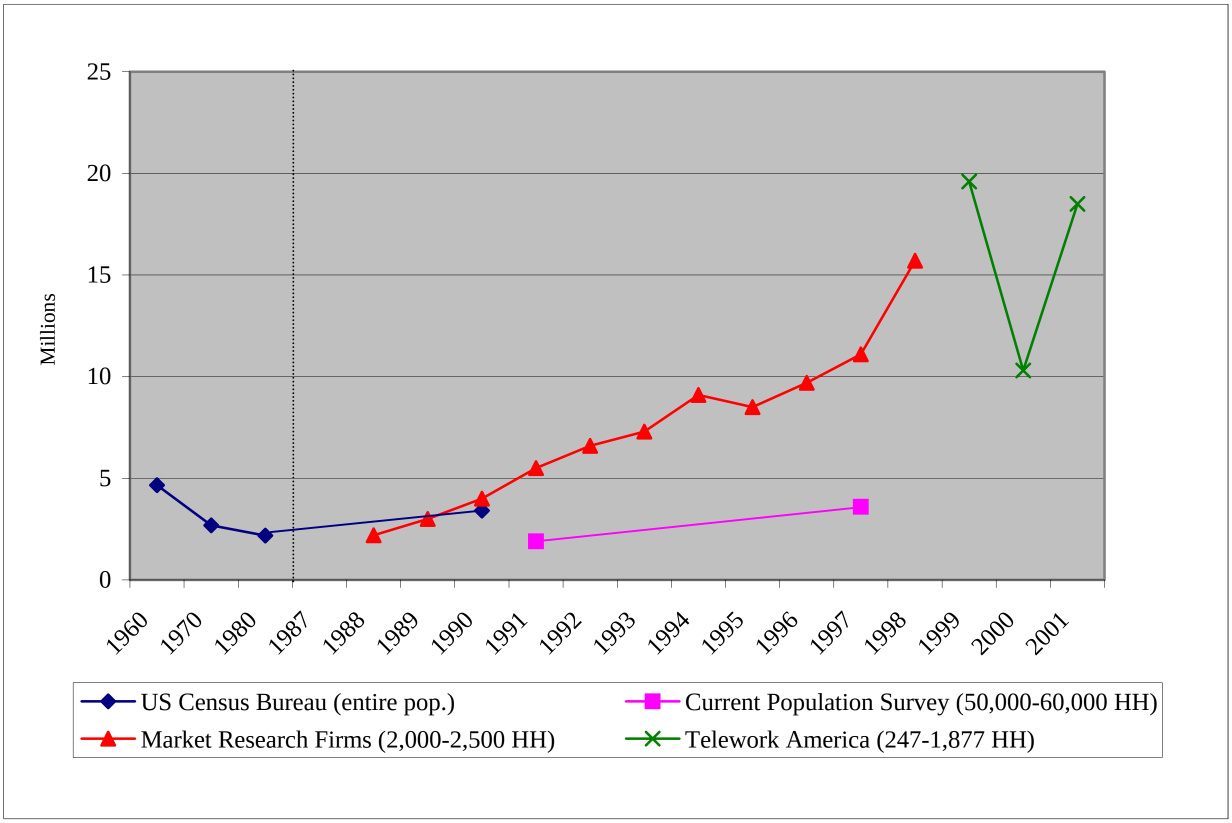


CPI for transportation (1996=100, min: 22.6, max: 101.0)



Population (thousands, min: 196,560, max: 272,691)

Figure 1. Time Trends of Selected Variables



Notes:
The years before 1987 (on the left side of the dotted vertical line) are free scale on the x-axis.
The numbers in parentheses indicate the range of the sample sizes for the corresponding surveys.

Figure 2. The Number of Telecommuters

Table 1. Multivariate Time Series Models for Vehicle-Miles Traveled (VMT) (N = 33)

Model	Adjusted R^2	Durbin-Watson statistic	Explanatory variables							
			Constant	Real GDP per capita	Real disposable income per capita	Real gasoline price	Miles per gallon	CPI (all)	CPI (transportation)	Population
VMT										
Alt. 1	0.555	1.668	0.0739 (7.930)	0.257 (3.968)		-0.0490 (-4.130)				
Alt. 2	0.582	1.752	0.0957 (4.291)	0.286 (4.249)		-0.0417 (-2.975)	0.181 (1.964)	-0.416 (-1.569)		
Alt. 3	0.601	1.920	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	1.572	0.0663 (4.432)	0.332 (3.191)		-0.0761 (-4.000)				
Alt. 2	0.509	1.612	0.0521 (2.935)		0.472 (3.362)	-0.0658 (-3.354)				
Alt. 3	0.488	1.697	0.144 (3.814)		0.481 (3.282)		0.260 (1.781)	-1.226 (-3.135)		
Alt. 4	0.556	1.856	0.134 (3.884)	0.348 (3.333)		-0.0509 (-2.340)	0.298 (2.084)	-1.004 (-2.443)		
Alt. 5 (recommended)	0.649	1.856	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.

Table 2. Telecommuting Models for VMT Residuals (N = 11)

Model	Adjusted R^2	Durbin-Watson statistic	Explanatory variables	
			Constant	Natural log of the number of telecommuters (in millions)
VMT				
Alt. 1	0.550	2.362	0.0988 (4.073)	-0.0450 (-3.636)
Alt. 2	0.289	2.308	0.0754 (2.643)	-0.0328 (-2.250)
Alt. 3	0.319	2.005	0.0731 (2.452)	-0.0363 (-2.383)
VMT per capita				
Alt. 1	0.628	2.122	0.143 (3.945)	-0.0781 (-4.232)
Alt. 2	0.591	1.708	0.136 (3.888)	-0.0703 (-3.934)
Alt. 3	0.410	1.702	0.118 (3.009)	-0.0566 (-2.818)
Alt. 4	0.438	2.208	0.118 (2.829)	-0.0632 (-2.968)
Alt. 5 (recommended)	0.273	2.173	0.102 (2.284)	-0.0499 (-2.183)

Notes:
Each dependent variable comprises the residuals of the corresponding estimated time series model in Table 1.
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.

Table 3. 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 4. 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.