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What Drives Telecommuting?

The Relative Impact of Worker Demographics, Employer Characteristics, and Job Types

Margaret Walls, Elena Safirova, and Yi Jiang

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

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Abstract

We analyze a 2002 survey of Southern California residents to evaluate the relative importance of factors that affect workers' propensity to telecommute and telecommuting frequency. The survey collected a wealth of individual demographic information as well as job type, industry, and employer characteristics from about 5,000 residents. In agreement with previous studies, we find that the propensity to telecommute is increasing with worker age and educational attainment. At the same time, we conclude that the propensity to telecommute depends to a large extent on a worker's job characteristics and that the quantitative effects of job characteristics are at least as important as demographic factors.

We also study what factors affect telecommuting frequency based on a one-week commuting diary of the telecommuters in the survey. The industry and occupation categories that play a significant role in affecting propensity to telecommute do not have similar effects on telecommuting frequency. On the contrary, some other job-related factors show substantial influences.

Key Words: telecommuting, telework, transportation planning, econometric estimation, telecommuting frequency, telecommuting propensity

JEL Classification Numbers: C35, J22, R41

Contents

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Introduction

Transportation planners, environmental policymakers, and worker advocates have long espoused the virtues of telecommuting. Working at home or at a "telecenter" instead of at a traditional employer's workplace has been touted as an easy way of getting cars off the roads, reducing congestion and air pollution, and improving the job satisfaction of millions of workers.

However, estimates of the extent of telework nationwide are quite low. In a survey of several studies, Handy and Mokhtarian (1995) find that, on average, on a given workday, only 1.0–2.1 percent of the workforce telecommutes. Numerous studies have looked at the factors that explain telecommuting choice and frequency, but most of those studies rely on small datasets from single employers and many do not include a control group of nontelecommuters (Walls and Safirova 2004). With metropolitan planning organizations in some areas implementing policies that encourage employers to provide telework incentives to their employees, and with national telework tax credit legislation recently introduced in Congress, it is critical that we better understand what motivates people to work from home.[1] Such an understanding would help transportation planners improve their modeling of trip generation and allow policymakers to better target incentive programs. In addition, employers may gain a better understanding of the telecommuting potential of their workforce.

In this study, we use a 2002 survey of Southern California residents to evaluate the factors that explain a worker's propensity to telecommute and the frequency with which he or she telecommutes. The survey, sponsored by the Southern California Association of

*Walls and Safirova are senior fellow and fellow, respectively, at Resources for the Future, and Yi Jiang is a Ph.D. student at the Department of Economics of the University of Maryland.

[1] Businesses that operate in the South Coast Air Quality Management District in California are subject to Rule 2202, which mandates reductions in emissions from employee work trips. See http://www.aqmd.gov/rules/reg/reg22/r2202.pdf for text of the rule. Senator Rick Santorum (R-PA) introduced federal telecommuting legislation in 2005. See http://santorum.senate.gov/public/index.cfm?FuseAction=PressOffice.View&ContentRecord_id=1279&CFID=10822000&CFTOKEN=58575626.

Governments (SCAG), collected responses from more than 5,000 residents of the Southern California region, 55 percent of whom were in the workforce; approximately 679 of these workers said that they had worked from home or at a location other than their regular workplace at least one day in the past two months. A wealth of individual demographic information was collected in the survey, as well as employer- and job-related data. The latter is a point of emphasis for us and allows us to contribute significantly to the literature on telecommuting. Some of the smaller telecommuting studies using data from a limited number of employers often incorporate information about employers, jobs, and the workplace environment. But large survey datasets usually do not have good employer and job information. The SCAG survey is thus an improvement on the status quo. In addition, the SCAG survey was careful to separate home-based business owners from true employee telecommuters and to find the number of jobs the respondent held and whether the worker was an independent contractor. These are issues that have been emphasized by Pratt (2000), and previous surveys have not adequately identified these types of workers.

In the next section, we present a very brief review of the literature on telecommuting. We then discuss the SCAG survey dataset and present some summary statistics of the variables we include in our model. Following sections present the propensity and frequency results, and we close with concluding remarks.

Literature on Telecommuting Choice and Frequency

Walls and Safirova (2004) survey the literature on telecommuting choice and frequency, as well as studies that focus on vehicle miles traveled and air pollution impacts of telecommuting. We report here only on the studies most similar to our own—that is, those that rely on large survey datasets across multiple employers and that use econometric techniques to estimate a model of the likelihood that a worker will telecommute and/or the number of days spent telecommuting per week.[2]

Drucker and Khattak (2000) use the 1995 Nationwide Personal Transportation Survey (NPTS) to econometrically estimate the propensity to work from home. The NPTS provides a large national sample of individuals working a variety of jobs. It focuses on general travel

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[2] Some that rely on smaller datasets across fewer employers or on stated preference surveys are Bernardino and Ben-Akiva (1996), Sullivan, Mahmassani, and Yen (1993), and Mokhtarian and Salomon (1997).

behavior and vehicle ownership but also gathers a host of sociodemographic data and asks respondents how often they had worked from home in the previous two months. The choices available were two or more times per week, about once per week, once or twice per month, less than once a month, or never.[3]

A drawback of the NPTS is the lack of job or employer information. As it is primarily a travel survey, it focuses on questions related to vehicle ownership and driving, and does not survey people about their jobs. It does, however, include a wealth of socioeconomic and demographic information and is one of the few large national samples available for study.

Drucker and Khattak find that the greater the level of education an individual has and the older he or she is, the more likely he or she is to work at home. Males are more likely to work at home than females, and people with children under the age of six are more likely to work at home than people without children. The likelihood of working at home increases with household incomes, but the marginal effects are relatively small. Respondents living in rural areas are more likely to work from home than those living in urban areas. Workers who must pay to park at work and those with less access to transit are more likely to work from home. A somewhat surprising finding is that distance to the job site is negatively correlated with working at home–that is, the farther individuals live from their job, the less likely they are to work at home.

The lack of information on job type and tenure, as well as employer characteristics, means that some of the individual characteristics in the Drucker and Khattak model are probably proxying for other factors. For example, the gender, age, education, and income variables may all substitute for things like job tenure and whether the position the employee holds is a professional, management-level job.

Popuri and Bhat (2003) use data from a 1997–1998 survey of 14,441 households in the New York metropolitan area conducted by the New York Metropolitan Transportation Council and the New Jersey Transportation Planning Authority. 11,264 households completed travel diaries, and out of these, the authors were able to use 6,532 employed individuals in their final sample. In the final sample, 1,028 people—15.7 percent of the total—reported that they telecommuted.

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[3] Although it is not clear whether these are true teleworkers or home-based business owners whose main place of work is at home, Drucker and Khattak feel that they are teleworkers because answers to the question on whether respondents "mainly" work from home barely overlapped with the answers from the question on frequency of working at home.

The authors estimate a model of telecommuting choice and frequency. Results show that the following factors increase the likelihood that an individual telecommutes and increase the average number of days per week telecommuted: a college education, a driver's license, being married, working part-time, working for a private company (rather than government), and having to pay to park at work. The study also found that women with children are more likely to telecommute and do so more days per week, but women without children are less likely to telecommute than men. The higher the household income, the more likely individuals are to telecommute and the more days they do so. Also, the longer individuals have worked at their current places of employment, the greater the probability they telecommute. Unfortunately, the authors do not have available a variety of other job-related variables that would possibly be significant. This means that, as in the Drucker and Khattak study, some of the demographic variables, such as education, are likely partially proxying for the job type.[4]

Description of SCAG Dataset

The SCAG 2002 Telework Survey was designed to establish a benchmark of the percentage of the population that teleworks in the SCAG region.[5] A total of 5,028 interviews were completed with households in the six-county SCAG region. Data collection was conducted by telephone using random digit dialing technology and took place from June to August 2002. The consulting firm NuStats, Inc., was engaged by SCAG to develop the survey instrument, collect the survey data, and prepare some initial data analysis.

Of the 5,028 respondents surveyed, 2,766, or 55.0 percent, were in the workforce. Of these workers, 68.4 percent were employee non-teleworkers—that is, respondents who said that they had not teleworked at all in the past two months; 24.6 percent were employees who reported that they had teleworked at least once in the past two months; and 7.0 percent were home-based business owners. The survey collected data on income, education, respondent age, number and

[4] Popuri and Bhat include some variables in the model that are likely to be endogenous. These are dummies for whether the individual drives to work, takes public transit to work, has a fax machine at home, and has multiple phone lines at home. The latter two may be jointly chosen along with the telecommuting decision, and the mode choice variables—the driving and transit dummies—obviously reflect decisions made by the individual that are likely to be functions of individual characteristics such as education and income. Inclusion of these endogenous variables may be biasing the Popuri and Bhat results.

[5] SCAG functions as the metropolitan planning organization for six counties: Los Angeles, Orange, San Bernardino, Riverside, Ventura, and Imperial.

ages of children, ethnicity, and other sociodemographic information. It also collected information about the industry in which the respondent was employed, the kind of work the respondent did, tenure with employer, tenure with current supervisor, size of firm, and some other job-related data.[6] In Table 1, we present summary statistics for variables that we use in the econometric model in the following sections. Some observations have missing data for some variables; our final sample size used in the propensity analysis includes 2,315 workers and 608 telecommuters, and 499 telecommuters are used in the frequency analysis.

An important feature of the SCAG survey is that it asks respondents about their working status and places of work on every weekday of the week prior to the survey. Respondents' choices include home; an employer's site a telework center; an employer's satellite office; a client or customer site; out of town; and in a car, bus, train, plane, or other transportation. The respondent could also reply that he or she did not work on that particular day. Multiple answers are allowed. With this information, we can calculate how many days the respondents worked in that week, how many places they worked, and whether they telecommuted on each day of the week. Adopting a relatively broad definition of telecommuting, we consider an individual to have telecommuted on a particular day if he or she worked at one of three places: home, telework center, or employer's satellite office. Even if he or she also worked at other places, we consider the day to be a telecommuting day. Aggregating the daily counts across the weekdays, we get the number of telecommuting days for each person during the week.

Using the weekly diary data to measure the telecommuting frequency has some advantages and disadvantages compared to the existing literature. Frequency variables used in previous studies were all collected from a general question such as "How often had you worked from home during the previous two months?" The answers to this type of question would have been based on respondents' memory and quick estimation. The measurement errors could be extensive and in some cases substantial. Instead, individuals in our sample were asked about their past week experience, which should be recalled more accurately than if recalling a longer period. On the other hand, the weekly diary might not be representative of a respondent’s commuting behavior. In the section “Explaining Telecommuting Frequency,” we explain how we attempt to control for this problem in our estimation technique.

[6] Descriptive analysis of the dataset can be found in Safirova and Walls (2004)

Table 1 defines the variables from the SCAG dataset that we use in the model, and Table 2 presents means and standard deviations for those variables. The means and standard deviations are reported separately for telecommuters and nontelecommuters, and some results are suggested by comparing the columns. For example, more nontelecommuters are under age 30, have no college degree, and are nonwhite. Survey respondents are spread across different industries and job types, and although it is difficult to see strong differences in the telecommuter and non-telecommuter means, some results do stand out. For example, the mean numbers of telecommuters who have job types 6 and 9 (education and training and sales, respectively), are substantially higher than the means for nontelecommuters in those categories. The econometric results in the next section will address these factors.

Explaining the Propensity to Telecommute

In this section, we model the probability that a worker in the sample telecommutes any day in the two months before the survey was taken. We assume there is a linear expected utility a worker gets from telecommuting:

$$(1) \quad EU_i = X_i\beta + Z_i\gamma + \varepsilon_i$$

where X_i is a vector of household and individual characteristics and Z_i is a vector of industry and job-related variables for person *i*. ε_i is identically and independently distributed as a standard normal with mean zero and variance one. The latent variable EU_i is not observed directly. Instead, the decision whether or not to telecommute is observed through the survey instrument. Thus, for each person we define:

$$(2) \quad \begin{array}{ll} Y_i = 0 & \text{if } EU_i < 0 \\ \text{and} & \\ Y_i = 1 & \text{if } EU_i \geq 0 \end{array}$$

where Y_i is a dummy variable indicating whether or not worker *i* telecommutes. Then, the probability that Y_i equals one is

$$(3) \quad \begin{aligned} \Pr(Y_i = 1 \mid X_i, Z_i) &= \Pr(EU_i \geq 0 \mid X_i, Z_i) \\ &= \Pr(\varepsilon_i \leq X_i\beta + Z_i\gamma \mid X_i, Z_i) \\ &= \Phi(X_i\beta + Z_i\gamma) \end{aligned}$$

where $\Phi(\cdot)$ is the cumulative function of a standard normal distribution. This is a standard probit model that can be estimated by a maximum likelihood estimation technique.

We pay particular attention to the industry and job variables, Z_i, because many large survey studies such as ours do not have access to such variables. Table 2 shows the results of the probit model estimated in two ways: column 1 shows results of the full model and column 2 the results obtained when we omit all of the industry and job variables. A Wald test of the joint significance of these latter variables is performed; the test statistic is shown in the bottom row of Table 3 (Greene 2003). Based on the test statistic, we can strongly reject the hypothesis that the worker and household demographic variables alone explain the choice to telecommute. The industry and job-related variables add explanatory power to the model. We focus on the results in column 1 for the remainder of this discussion. For ease of interpretation, instead of coefficient estimates of the probit model, the table shows the marginal effects of each variable.[7]

Demographic variables. We find that a worker is more likely to telecommute if he or she is over 30, has a college degree, and is Caucasian. He or she is also more likely to telecommute if there is at least one other adult in the household. On the other hand, having children makes it less likely that a person will telecommute, though the effect is only statistically significant for children between 6 and 17 years old and not for families with younger children. There is no statistically significant difference between male and female workers in the propensity to telecommute.

By looking at the marginal effects of each variable, we can evaluate the relative impacts of the different variables. The results indicate that having a college degree is quite important in explaining telecommuting. Even controlling for industry, job types, job tenure, and other factors that we describe in the next section, people with higher educational achievement are more likely to telecommute. We estimated the model with variations on the education variable, including separate dummy variables for high school diploma, some graduate school, and a graduate degree but found that the strongest results were obtained by simply including an indicator for college degree.

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[7] The marginal effect of the *k*th variable X_k on the probability of $Y=1$ in a probit model is

$$\frac{\partial \Pr(Y=1|X)}{\partial X_k} = \phi(X\beta)\beta_k ,$$

where $\phi(\cdot)$ is the density function of the standard normal distribution. Obviously, this marginal effect has the same sign as β_k, and the value of the marginal effect depends on *X*. This in turn means that each observation has its own marginal effect. By convention we present here marginal effects evaluated for an "average" person. That is a person taking sample means of every explanatory variables. We also have mean marginal effects computed and available from the authors upon request, which are marginal effects averaged across all individuals in the sample. We find that these two sets of marginal effects are sufficiently close to each other in significance and magnitude.

The gender and children variables may be surprising, given the pervasive view in the popular press that telecommuting appeals to families with children. The findings are also at odds with those of the Drucker and Khattak and Popuri and Bhat studies summarized above. However, our findings are robust to different model specifications. They do not change if we include the number of children in the household rather than dummy variables, or an interaction between the gender dummy and the number of children or the children dummies. We consistently find that there is no difference between male and female workers in the propensity to telecommute. And we also find that workers in households without children are more likely to telecommute than those with children, though the effect is only marginally significant in all model specifications.

We do not include household income as an explanatory variable. Income is highly correlated with age, education, and our job variables; thus the results are improved if we leave this variable out.

Industry and Job-related Variables. The first 10 industry and job variables in Table 3 are dummy variables that are equal to 1 if the survey respondent works in a particular industry. The industries are as defined in Table 1; the omitted industry in the probit model is the "other" category in the questionnaire along with wholesale trade, aerospace, and military.[8] The next four variables are dummy variables for firm size. The survey asked people what the number of employees was at their "main work site." The omitted size dummy is the smallest, fewer than 25 employees; the four dummies then are for 25–99 employees, 100–249, 250–499, and more than 500.

Three of our industry dummies are statistically significant in explaining the propensity to telecommute. We find that workers in the transportation or communication industry are approximately 10 percent less likely, and workers in retail trade 11 percent less likely, to telecommute than workers in wholesale trade, aerospace, military, and other industries. Workers in consulting are more likely to telecommute. There are no statistically significant differences among the other industries.

Two of our firm size dummy variables are statistically significant. People who work in the smallest firms, those with fewer than 25 employees, are more likely to telecommute than the next two size categories: 25–99 employees and 100–249 employees. However, the two largest

[8] There are fewer respondents in these categories than the others; thus we group them with the "other" category. The results are not different if we include separate dummy variables for these groups.

firm size dummies are not statistically different from the very smallest. These results seem to indicate that the very smallest businesses have a great deal of flexibility in how and where their employees perform their jobs, whereas the largest companies may have formal teleworking opportunities. Those in the middle—firms that have between 25 and 250 employees—provide fewer opportunities for their employees to telecommute.

After the industry variables in the table are variables related to kinds of jobs. We include a dummy variable equal to 1 if the respondent is a full-time employee and a dummy equal to 1 if the respondent is a part-time employee; the omitted dummy includes contract workers and those who are self-employed outside the home.[9] We also include the number of years that the respondent has worked for his or her current employer. Following that variable are 10 dummies for job categories.

The full-time and part-time employee dummies are strongly significant in explaining telecommuting. Both full-time and part-time employees are approximately 19 percent less likely to telecommute than are contract and self-employed workers. These results indicate that the latter categories of workers are more flexible about where they perform their job tasks and thus work at home more than employees.

Five of the job type variables are significant. The omitted job type category includes social services, public safety, military, and other job types not listed in the questionnaire. By comparison with this group, workers with jobs in health care are less likely to telecommute. This makes sense because this group includes doctors and nurses who must work in hospitals or see patients in offices. Workers with the following types of jobs are more likely to telecommute: architecture and engineering and other professional, education and training, sales, and senior and middle management. Sales jobs often include travel and work outside of a traditional office or other workplace, thus this result is not surprising. Workers who classify themselves as having a job in sales are nearly 16 percent more likely to telecommute, all else equal, than workers with jobs in social services, public safety, military, and other categories. It is somewhat surprising that workers in senior and middle management are more likely to telecommute, all else equal, because they presumably must supervise other workers. Results indicate, however, that they are about 11 percent more likely to telecommute than the baseline category of workers.

[9] As explained above, we omit home-based business owners from our study.

The variable TENURE, which measures the length of time, in years, that the respondent has worked for his or her current employer, is not statistically significant. The survey also asked about the length of time that the respondent had worked for his or her current supervisor; this variable was also not significant. These results are somewhat surprising, as it seems plausible that telecommuting, which is generally considered a fringe benefit, would be more commonly offered to workers in longer standing with a company.

Explaining Telecommuting Frequency

As discussed above, the weekly diary gives us a relatively accurate way to measure telecommuting frequency based on the week just prior to the survey. We can count the number of days per week an individual telecommutes—assuming the surveyed week is a representative week for that person. For some individuals, however, that week does not look representative. For instance, 42 out of the 679 telecommuters indicate that they did not work at all in the prior week. We removed these people from our analysis.

For the rest of the sample, the number of telecommuting days is bounded from above by the number of working days for that individual in that week. Moreover, some individuals did no telecommuting in that particular week, but we know that they are telecommuters because they responded that they had telecommuted at least one day in the previous two months. It is likely that these people telecommute, on average, less than one day a week. Similarly, an individual who telecommutes five days in the surveyed week is not necessarily a full-week telecommuter. It is more plausible to regard him or her as a high-frequency telecommuter. In general, the non-representative week problem makes it more sensible to interpret the counts of telecommuting days on an ordinal rather than a cardinal basis. In other words, people who report that they telecommuted two days in the previous week may not routinely telecommute twice as much as people who report one day of telecommuting, but we accept that they do telecommute more frequently than the latter group.

To overcome these survey problems, we do three things. First, we control for the number of days worked in our regression analysis. Everything else equal, a positive coefficient on the number of working days variable implies that individuals increase telecommuting frequency when they work more days per week. Second, we recode the counts into either binary or three-level measures of telecommuting frequency. People who telecommute one day or less are characterized as infrequent telecommuters. Those telecommuting two or three days are labeled as medium-level telecommuters, and those telecommuting more than three days as high-frequency telecommuters in the three-level measure; in the two-level (binary) measure, anyone telecommuting 2 or more days is considered a frequent telecommuter. Table 4 shows the distributions of telecommuters according to our two frequency measures. Third, we use the ordered probit model to analyze the frequency [10]. An ordered probit model treats the dependent variable as an ordinal variable rather than a cardinal one. A simple ordered probit model is outlined as follows.

Individuals have different choices regarding telecommuting frequency, represented by $\{1,2,\ldots,J\}$ where a larger number means higher frequency. The net utility of person i with some amount of telecommuting, denoted as Y_i^*, is determined as

$$Y_i^* = X_i\beta + u_i ,$$

where X_i represents a set of individual, household, and job-related characteristics and u_i is random individual heterogeneity following a standard normal distribution. Rather than Y_i^*, we observe person i's choice of telecommuting frequency, y_i. Let $\alpha_1 < \alpha_2 < \ldots < \alpha_{J-1}$ be unknown threshold values, and assume

$$y_i = 1, \text{ if } Y_i^* \le \alpha_1 ,$$

$$y_i = 2, \text{ if } \alpha_1 < Y_i^* \le \alpha_2 ,$$

$$\vdots$$

$$y_i = J, \text{ if } Y_i^* > \alpha_{J-1} .$$

The probabilities of choosing each level of frequency given X_i are computed as

$$\Pr(y_i = 1 \mid X_i) = \Pr(Y_i^* \le \alpha_1 \mid X_i) = \Pr(X_i\beta + u_i \le \alpha_1 \mid X_i) = \Phi(\alpha_1 - X_i\beta) ,$$

$$\Pr(y_i = 2 \mid X_i) = \Pr(\alpha_1 \le Y_i^* \le \alpha_2 \mid X_i) = \Phi(\alpha_2 - X_i\beta) - \Phi(\alpha_1 - X_i\beta) ,$$

$$\vdots$$

$$\Pr(y_i = J \mid X_i) = \Pr(Y_i^* > \alpha_{J-1} \mid X_i) = 1 - \Phi(\alpha_{J-1} - X_i\beta) .$$

The model is estimated by maximum likelihood. When $J = 2$, the model reduces to the binary probit model.

We first estimate a probit frequency model with the Heckman correction for selection (Heckman 1979). This model accounts for the possibility that the unobserved factors that explain

[10] We also tried the ordered logit model, which yields highly similar results.

the propensity to telecommute also explain the frequency of telecommuting. The independence tests fail to reject the hypothesis that the telecommuting propensity and frequency are two normally independent decision processes. Therefore, we estimate our frequency models thereafter independent from the propensity model. Individuals who have missing values in any of the explanatory variables or did not work in that week are removed from the analysis. This results in a sample of 499 observations.

In addition to the explanatory variables used in the propensity model, we also include several job-related variables that were only collected for telecommuters (see Table 1). For instance, we add dummy variables for whether the employer has a formal telecommuting program, whether the employer offers a compressed work week schedule, and whether the employee has work space at the employer's job site, as well as a variable measuring the years of telecommuting experience, the two-way commuting time, and others. Section B in Table 2 provides the summary statistics of these extra variables.

Although we estimated the ordered probit model using different measures of telecommuting frequency, we find that the results are highly consistent across the different measures. Given space limitations, we present the estimates for the three-level frequency measure in Table 5. Column (1) of Table 5 shows the estimated coefficients and standard errors.

Results suggest that education has a strong positive impact on telecommuting frequency, as it did on the propensity to telecommuting. Age is also significant, but no other individual or household characteristics have significant effects on the frequency of telecommuting. In contrast to the propensity model, neither industry nor occupation nor firm size has an effect on telecommuting frequency. We again perform a Wald test of the joint significance of these variables, as we did in the propensity model, but here we cannot reject that these variables are jointly insignificant. Nevertheless, other job-related variables, especially those new ones, exhibit interesting impacts on the frequency of telecommuting. As expected, people working more days also do more telecommuting. Full-time employees telecommute less than the omitted category: the self-employed workers and contractors. Employers' formal telecommuting programs promote more frequent telecommuting than does the informal agreement between employee and supervisor. And last, multiple jobs and longer round-trip commute times are associated with more telecommuting. Part-time work status, tenure with current employer, overtime work, a fixed telecommuting schedule set by employer, a compressed week, and telecommuting experience do not have significant impacts on telecommuting frequency. No workspace at an employer's job site leads workers to telecommute more days per week, though the effect is marginal.

To facilitate quantitative interpretation of the effects of the variables on telecommuting frequency, we convert the coefficients to marginal effects, which vary by the choice of interest (i.e., the frequency of telecommuting).[11] Column (2) of Table 5 shows the marginal effects of changes in explanatory variables on the probability of being a high-frequency telecommuter for a sample-average individual. According to Column (2), everything else equal, a person age 30 or younger is 9 percent less likely to be a high-frequency telecommuter than a person older than 30. A person without a college degree is 10 percent less likely to be a high-frequency telecommuter than a person with a college (or higher) degree. Providing office space to telecommuters who do not have any will induce about 12 percent of telecommuters to leave the high-frequency group to a lower group. Telecommuters who work for a company with a formal telecommuting program are 22 percent more likely, on average, to be high-frequency telecommuters.

Our results show that it is somewhat difficult to explain the frequency with which people telecommute given the data in the survey. Many of our variables are insignificant. Those work-related variables that are significant suggest that additional information would perhaps be useful to gain a full understanding of telecommuting behavior. In addition, although the survey's focus on the prior week has some advantages over previous studies, it highlights the fact that a diary kept over a period of time would perhaps be more useful.

Conclusions

Very few comprehensive datasets address telecommuting behavior across a wide range of individuals holding jobs with different employers. The 2002 Telework Survey designed and administered by the Southern California Association of Governments is one such survey. It compiled a wide range of socioeconomic and demographic data on individuals, as well as data on job types and some employer characteristics. It also is one of the few surveys to be very careful about identifying true telecommuters: home-based business owners are separated from true employee teleworkers. In this study, we used the data to econometrically model the propensity to telecommute and the frequency of telecommuting. Because the survey is one of the few with good job and employer information, we focus our attention on the relative impacts of those variables on telecommuting behavior.

[11] The marginal effects of each explanatory variable on the probabilities of all choices sum to zero.

We find that where an individual works and what kind of job he or she holds is quite important in explaining the likelihood that he or she telecommutes. Particular industries appear to be more likely to have telecommuters, and certain types of jobs are more conducive to telecommuting, in particular jobs in sales, education and training, and architecture and engineering. In contrast, some jobs—for example, those in health care—are less conducive to telecommuting. Individuals who work at mid-size firms (those with 25–250 employees) are less likely to telecommute than individuals who work at very small (< 25 employees) or very large firms (> 250 employees). Somewhat surprisingly, we find that the length of time that an individual has worked for his current employer or been with his current supervisor does not affect the likelihood of telecommuting.

Explaining the frequency of telecommuting appears to be more difficult. Although this dataset is an improvement in some ways on previous datasets, it seems to fall short in some respects. The survey asked individuals about their place of work on each day of the week prior to the survey. This means that there is a good chance that the responses about telecommuting frequency are accurate. However, the week in question may not be representative of an average week and thus could provide some misleading results. One strong finding we get is that whether or not the employer has a formal telework program seems to be a strong determinant of telecommuting frequency. Other job and work-related variables are not statistically significant.

Finally, in terms of demographic variables, our findings are consistent with some previous studies in that we find that education, age, and race are all statistically significant in explaining telecommuting behavior. However, unlike some previous studies, we do not find a statistically significant effect from gender—that is, women are no more likely to telecommute than are men. Furthermore, the presence of children in the household does not seem to affect telecommuting in any measurable way.

The length of time it takes an individual to commute to and from work, as reported by the individual in the survey, seems to significantly affect telecommuting frequency. In the future, we plan to explore this result further by combining the survey data with more geographic and spatial information, including information on the degree of congestion in the region. Further understanding of the factors that determine telecommuting will be of much use to local transportation planners and federal transportation and environmental policymakers attempting to reduce vehicle travel, congestion, and emissions.

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Tables

Table 1. Econometric Model Variables

Variable	Definition
AGE30	Age dummy = 1 if 30 or younger, 0 otherwise
NO_COLLEGE	Education dummy = 1 if no college degree, 0 if college degree
WHITE	Ethnicity dummy = 1 if non-Hispanic white, 0 otherwise
KIDS_0-5	Dummy = 1 if at least one child under age six, 0 otherwise
KIDS_6-17	Dummy = 1 if at least one child between ages 6 and 17, 0 otherwise
OTHER_ADULT	Dummy = 1 if at least one other adult in the household, 0 otherwise
FEMALE	Gender dummy = 1 if female, 0 if male
FULL-TIME	Employment status dummy = 1 if full-time employee
PART-TIME	Employment status dummy = 1 if part-time employee
OVER-TIME	Overtime dummy = 1 if full-time and work more than 40 hours per week
TENURE	Years of work for the current employer
INDUS0	Dummy = 1 if respondent works in “all other industries”
INDUS1	Dummy = 1 if respondent works in construction industry
INDUS2	Dummy = 1 if respondent works in manufacturing industry
INDUS3	Dummy =1 if respondent works in transportation or communication industry
INDUS4	Dummy = 1 if respondent works in retail trade industry
INDUS5	Dummy = 1 if respondent works in finance, insurance, or real estate
INDUS6	Dummy = 1 if respondent works in arts and entertainment industry
INDUS7	Dummy = 1 if respondent works in health care
INDUS8	Dummy = 1 if respondent works in education services industry
INDUS9	Dummy = 1 if respondent works in consulting
INDUS10	Dummy = 1 if respondent works in government
JOB_TYPE0	Dummy = 1 if respondent’s job type is “all other occupations”

Variable	Definition
JOB_TYPE1	Dummy = 1 if respondent’s job type is construction, maintenance and repair, and production
JOB_TYPE2	Dummy = 1 if respondent’s job type is secretarial and administrative support
JOB_TYPE3	Dummy = 1 if respondent’s job type is finance and accounting
JOB_TYPE4	Dummy = 1 if respondent’s job type is architecture, engineering, or other professional
JOB_TYPE5	Dummy = 1 if respondent’s job type is information services, public relations, and customer services
JOB_TYPE6	Dummy = 1 if respondent’s job type is education and training
JOB_TYPE7	Dummy = 1 if respondent’s job type is health services
JOB_TYPE8	Dummy = 1 if respondent’s job type is consulting
JOB_TYPE9	Dummy = 1 if respondent’s job type is sales
JOB_TYPE10	Dummy = 1 if respondent’s job type is senior management or middle management
EMPL_0-24	Firm size dummy = 1 if fewer than 25 employees at work site
EMPL_25-99	Firm size dummy = 1 if 25-99 employees at work site
EMPL_100-249	Firm size dummy = 1 if 100-249 employees at work site
EMPL_250-499	Firm size dummy = 1 if 250-499 employees at work site
EMPL_500+	Firm size dummy = 1 if 500 or more employees at work site
OFFICE	Dummy = 1 if no work space at employer's site, 0 otherwise
FIXED_SCHED	Dummy = 1 if work at home by fixed schedule set by employer, 0 otherwise
COMP_WEEK	Dummy = 1 if employer offers compressed work week, 0 otherwise
FORMAL_TELE	Dummy = 1 if employer offers formal telework, 0 otherwise
COMMUTE_TIME	Two-way commuting time in minutes
YEARS_TELE	Years of telecommuting
DAYS_WORK	Number of days worked in the surveyed week
JOBS2+	Dummy = 1 if respondent has two or more jobs, 0 if one job

Table 2. Summary Statistics for Telecommuting Variables

A. Variables available for the whole sample				
Variable	*Telecommuters*		*Nontelecommuters*	
	Mean	*SD*	*Mean*	*SD*
AGE30	.127	.333	.264	.441
NO_COLLEGE	.334	.472	.643	.479
WHITE	.691	.463	.500	.500
KIDS_0-5	.230	.421	.272	.445
KIDS_6-17	.316	.465	.385	.487
OTHER_ADULT	.791	.407	.784	.411
FEMALE	.474	.500	.509	.500
FULL-TIME	.750	.433	.780	.414
PART-TIME	.089	.285	.177	.382
TENURE	7.45	6.68	6.43	6.25
INDUS0	.275	.447	.277	.448
INDUS1	.033	.179	.054	.226
INDUS2	.067	.251	.095	.293
INDUS3	.026	.160	.055	.228
INDUS4	.041	.199	.091	.287
INDUS5	.094	.292	.071	.258
INDUS6	.053	.223	.032	.177
INDUS7	.097	.296	.130	.336
INDUS8	.197	.398	.105	.306
INDUS9	.074	.262	.032	.175
INDUS10	.043	.202	.058	.234
JOB_TYPE0	.184	.388	.240	.427
JOB_TYPE1	.058	.233	.133	.340
JOB_TYPE2	.063	.242	.101	.301
JOB_TYPE3	.051	.220	.060	.238
JOB_TYPE4	.087	.282	.052	.221

A. Variables available for the whole sample				
JOB_TYPE5	.058	.233	.080	.271
JOB_TYPE6	.179	.384	.079	.270
JOB_TYPE7	.059	.236	.095	.293
JOB_TYPE8	.039	.195	.012	.108
JOB_TYPE9	.113	.317	.086	.280
JOB_TYPE10	.109	.311	.064	.245
EMPL_0-24	.398	.490	.340	.474
EMPL_25-99	.262	.440	.300	.458
EMPL_100-249	.146	.354	.167	.373
EMPL_250-499	.059	.236	.075	.263
EMPL_500+	.135	.342	.118	.323
N	608		1707	
B. Additional variables available for telecommuters only				
OVER-TIME	.545	.498	NA	NA
OFFICE	.092	.290	NA	NA
FIXED_SCHED	.100	.301	NA	NA
COMP_WEEK	.118	.323	NA	NA
FORMAL_TELE	.144	.352	NA	NA
COMMUTE_TIME	61.56	54.28	NA	NA
YEARS_TELE	5.70	5.79	NA	NA
DAYS_WORK	4.85	.540		
JOBS2+	.096	.295		
N[12]	499			

[12] Sample size is smaller because of missing values for these additional variables or because some respondents worked zero days in the surveyed week.

Table 3. Probit Model of the Likelihood of Telecommuting

Variable	(1)		(2)	
Individual and household characteristics	*Marginal effect*	*SE*	*Marginal effect*	*SE*
AGE30	-0.109***	0.022	-0.110***	0.020
NO_COLLEGE	-0.178***	0.022	-0.203***	0.018
WHITE	0.075***	0.019	0.102***	0.018
KIDS_0-5	-0.006	0.022	-0.012	0.021
KIDS_6-17	-0.045**	0.020	-0.047**	0.019
OTHER_ADULT	0.047**	0.022	0.026	0.022
FEMALE	0.002	0.021	-0.018	0.018
Industry and job characteristics				
INDUS1	-0.022	0.054		
INDUS2	-0.022	0.036		
INDUS3	-0.113***	0.035		
INDUS4	-0.103***	0.034		
INDUS5	0.040	0.043		
INDUS6	0.095*	0.055		
INDUS7	-0.004	0.043		
INDUS8	0.061	0.054		
INDUS9	0.099*	0.054		
INDUS10	0.049	0.039		
EMPL_25-99	-0.074**	0.022		
EMPL_100-249	-0.086**	0.024		
EMPL_250-499	-0.045	0.034		
EMPL_500+	-0.019	0.030		
FULL-TIME	-0.265***	0.041		
PART-TIME	-0.228***	0.020		
TENURE	-0.001	0.002		
JOB_TYPE1	-0.073*	0.038		
JOB_TYPE2	-0.020	0.038		

Variable	(1)		(2)	
JOB_TYPE3	-0.056	0.040		
JOB_TYPE4	0.104***	0.048		
JOB_TYPE5	0.007	0.042		
JOB_TYPE6	0.112*	0.061		
JOB_TYPE7	-0.088**	0.041		
JOB_TYPE8	0.128	0.084		
JOB_TYPE9	0.143***	0.047		
JOB_TYPE10	0.110**	0.045		
N	2315		2448	
Log likelihood	-1113.68		-1276.15	
Chi square(27) = 188.02. Prob > chi2 = 0.0000.				

*** Statistically significant at the 99 percent level.
** Significant at the 95 percent level.
* Significant at the 90 percent level.
Variables defined in Table 1.

Table 4. Distributions of Telecommuters by Frequency

Number of telecommuting days		*Binary measure*		*Three-level measure*	
0	258	Infrequent	312	Infrequent	312
1	54				
2	45	Frequent	187	Medium	72
3	27				
4	18			High	115
5	97				

Table 5. Ordered Probit Model of Telecommuting Frequency[1]

Variable	**(1)**		**(2)**	
Individual and household characteristics	*Coefficient estimate*	*SE*	*Marginal effect[3]*	*SE*
AGE30	-0.351*	0.193	-0.086**	0.042
NO_COLLEGE	-0.379***	0.145	-0.098***	0.035
WHITE	-0.016	0.130	-0.004	0.036
KIDS_0-5	-0.049	0.152	-0.014	0.041
KIDS_6-17	-0.048	0.128	-0.013	0.035
OTHER_ADULT	-0.154	0.145	-0.044	0.043
FEMALE	-0.057	0.137	-0.016	0038
Industry and job characteristics[2]				
FULL-TIME	-0.684***	0.207	-0.217***	0.072
PART-TIME	-0.330	0.281	-0.080	0.059
TENURE	0.003	0.012	0.001	0.003
OVER-TIME	0.069	0.147	0.019	0.041
OFFICE	0.390*	0.217	0.122*	0.075
FIXED_SCHED	-0.199	0.199	-0.051	0.047
COMP_WEEK	-0.123	0.196	-0.032	0.050
FORMAL_TELE	0.663***	0.162	0.216***	0.059
COMMUTE_TIME	0.003**	0.001	0.0007**	0.0003
YEARS_TELE	-0.003	0.014	-0.001	0.004
DAYS_WORK	0.332***	0.101	0.092***	0.029
JOBS2+	0.547***	0.200	0.177**	0.073
N	499			

[1]Explaining probability of infrequent (<2 days/week), medium (2–3 days/week), and high (≥4 days/week) levels of telecommuting.
[2]Industry, occupation and firm size dummies are not shown in the table since none of them is significant.
[3]Marginal effects of changes in the explanatory variables on the probability of being a high frequency telecommuter, for an average individual in the sample.
***Statistically significant at the 99 percent level.
**Significant at the 95 percent level.
*Significant at the 90 percent level.
Variables defined in Table 1.