The Impact of Telecommuting on the Journey to Work: A Two-Sample Instrumental Variables Approach

DISSERTATION CHAPTER

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ABSTRACT

Telecommuting is viewed as a public policy tool for reducing congestion and air pollution, but it may not be as effective as people think if workers who can telecommute choose to live (work) farther from their workplaces (homes) than non-telecommuters. Existing studies have not been able to fully address this issue because they all assume telecommuting is exogenous to commuting behavior. This study assembles information on telecommuting from the work schedule supplement to the May 2001 Current Population Survey (CPS) and information on commuting behavior from the 2000 Census 5% Public Use Micro-data Series (PUMS) and applies a two-sample instrumental variables technique to examining the impact of telecommuting on commute length and travel mode. I use the percent of workers who use the Internet when working at home in a person's two-digit occupation and MSA of the same size to instrument for telecommuting. The results show that telecommuting increases a married female worker's one-way commute time by 9–12 minutes. The impact on commute mode choice is positive and statistically insignificant.

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1 Introduction

Telecommuting reduces both the monetary and psychological costs of commuting. Employers, by allowing workers to telecommute, can recruit and retain valued employees and possibly reduce the costs of office space and administrative support. More importantly, telecommuting is increasingly suggested as a solution to traffic congestion and air pollution in urban areas. For instance, the Connecticut Department of Transportation established a statewide initiative "Telecommute Connecticut!" to help employers within the state set up and run telecommuting programs.[2] In May 2006, the U.S. Department of Transportation announced its new *National Strategy to Reduce Congestion on America's Transportation Network*, which highlights "Four Ts" – tolling, transit, telecommuting and technology – as an approach to reducing traffic congestion.

From the perspective of reducing congestion and pollution caused by vehicle miles traveled, a key policy question is what impact telecommuting has on total commute miles traveled.[3] At first blush it would appear that greater telecommuting should decrease commute miles. However, since telecommuting decreases the cost of commuting, it is plausible that telecommuting actually induces workers to work farther from home. For example, a woman who works at home one day a week

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[2] See their website http://www.telecommutect.com for more information about "Telecommute Connecticut!".

[3] The impact of telecommuting on non-commute VMTs is another important topic but is beyond the scope of the dissertation. In theory, telecommuting could affect non-commute VMTs in multiple ways. For example, flexible working schedules allow telecommuters to go shopping or run errands more often. If the individual changes home location in response to telecommuting, her/his demand for non-commute travel is likely to change as well. Walls and Safirova (2004) review a series of telecommuting papers and find no study show evidence of significant increase in non-commute travel for telecommuters. However, a common shortcoming of those studies is that they are based on small samples of workers.

reduces her commuting costs by 20% compared to a non-telecommuter. The decline in commuting costs provides an incentive for the woman to live farther away from her workplace or work farther from home.

Telecommuting may not achieve its policy objectives if it leads to a longer journey to work. However, it is not easy to obtain a consistent estimate of the causal impact of telecommuting on commute length. For research purposes, the ideal situation would be to randomly assign the opportunity to telecommute to a panel of workers and then examine how often they telecommute and the length of their commutes before and after the intervention. However, this type of experiments have never been performed. Because commute length and the decision to telecommute are jointly determined, estimates of the impact of telecommuting on travel time may be biased. Yet, the direction of the bias is unclear. On one hand, workers who have longer commute distances may be more likely to telecommute. At the same time, people who have a distaste for commuting would, all else equal, live closer to work as well as welcome a telecommuting opportunity.

In this paper, I examine the impact of telecommuting on total commute miles traveled while controlling for the endogeneity of the telecommuting decision. Because information on whether an individual telecommutes and the length of his commute are not contained in one data set, I utilize the two-sample instrumental variables (TSIV) technique developed by Angrist and Krueger (1992). The key data sets include the work schedule supplement to the May 2001 Current Population Survey (CPS) that contains telecommuting data, and the 5-percent Public Use Micro-data Series (PUMS) of the 2000 Census that contains information about one-way commute time and mode. An instrument is developed from the CPS sample that measures internet utilization for working at home for each 2-digit occupation and MSA-size combination. The instrument exploits the fact that certain occupations and MSA combinations are more open to telecommunication technology than others. These differences are by and large determined by job characteristics and internet infrastructure distribution, which, once I control for MSA and occupation fixed-effects, should be orthogonal to individuals' commutes. I also examine the effect of telecommuting on travel mode choice using the same method.

It is well documented in the literature that men and women exhibit distinct commuting patterns (White 1977, 1986), especially with respect to marital status and family composition. I conjecture that telecommuting might have differential effects on married women and single women for the following reasons. First, in a dual-earner household, the woman is more often the secondary earner rather than the primary. She is more likely than her husband to have a part-time or lower-paying job. Therefore, commuting costs, which will be reduced by telecommuting, may be more important to her workplace location than to her husband's. Second, the husband's job situation is likely to dominate the residential location of the household and affect the workplace location of the wife. Married women restrict the geographic ranges of their job search and often work closer to home than their husbands. People who are in occupations where telecommuting is an option will consider a larger range of workplace location than those who are not. Since married women may be more constrained in their job search than single women, telecommuting may have a larger impact on married women choosing workplace locations than on single women.

Therefore, I estimate each model for men, married women and single women separately to explore the heterogeneity in the response across these demographic groups.[4]

TSIV estimates demonstrate that telecommuting has a large positive effect on commute length for married female workers: Married women tend to work farther from home when they can substitute working at home for commuting. Being able to telecommute causes married women to increase their one-way commute an additional 9-12 minutes. This finding is consistent with the fact that married female workers have short commutes when telecommuting is not an option. The effect for male workers is smaller and statistically insignificant. For an average married women who works from home two out of five days a week, telecommuting reduces total commute miles, but not by 40 percent. My analysis also suggests that telecommuting is unlikely to affect the probability of a worker driving to work.

The rest of the paper is organized as follows: Section 2 defines telecommuting and provides background information about telecommuting and relevant studies. Section 3 presents baseline estimates of the "effect" of telecommuting on journey-to-work from OLS analysis of the 2001 Nationwide Household Transportation Survey (NHTS). Section 4 describes the identification strategy and the data. TSIV estimation results appear in Sections 5 and 6, with discussion and conclusions following in Sections 7 and 8.

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[4] It could be argued that women with children are more constrained in their choice of workplace location than women without children, regardless of marital status. When, however, the sample is split between women with and without children, the instrumental variable does not have enough explanatory power.

2 Urban Problems and Telecommuting

Traffic congestion is a problem for many urban areas in the US and around the world. The social costs of having millions of cars stuck in traffic are high. The Texas Transportation Institute estimates that, in 2003, congestion in the 85 largest urban areas in the US caused 3.7 billion vehicle-hours of delay, resulting in a cost of $63 billion. According to Lomax and Schrank (2005), each rush hour traveler pays an annual congestion tax of $800 to $1,600 in lost time and fuel in the 10 most congested areas of the US. The costs of congestion extend to the environment as well. Automobile emissions are an important source of ozone precursors—nitrogen oxides (NOx) and volatile organic compounds (VOCs). In 2003 more than 100 million people lived in counties that violated the federal ozone standard (EPA, 2004). This is a serious public health problem since it is well established that ozone can induce respiratory symptoms, and cause decrements in lung function and inflammation of the airways (EPA, 2003).

While pricing instruments such as congestion tolls and gasoline taxes are a way to internalize the external costs of driving, they are unpopular in the US. More attention has therefore been devoted to non-pricing strategies that control the demand for automobile travel directly. A subset of these strategies, Commute Trip Reduction (CTR) programs, focuses on commute trips, the largest contributor to rush hour traffic and one of the main contributors to the total vehicle miles traveled (VMT). These programs, often implemented through cooperation agreements between government authorities, employers and individuals, provide persuasion (e.g., Earth Day fairs), incentives (e.g., transit subsidies) and/or facilitate carpooling. Telecommuting is one of the most popular components of these programs (Pollution Probe 2001).

The literature has not settled on a consistent definition of telecommuting. Some studies include as telecommuters people who take work home and never substitute working from home for commuting on a work day. I refer to these people as teleworkers. Some research includes the self-employed who work at home sometimes as telecommuters. As a result, counts of telecommuters vary dramatically across studies. Mokhtarian et al. (2005) reviewed a number of papers using various data sets and concludes that the percentage of telecommuters in the late 1990s ranged from 3% to 20%. The latter figure includes the home-based self-employed and all teleworkers.

In this paper, I define *a telecommuter as an employee who works at home instead of traveling to a workplace at least one day every two weeks.* People who commute every day even though they sometimes work from home, as well as those who telecommute infrequently are not counted as telecommuters in my definition. My definition also excludes the self-employed since they are not the target population of TDM policy. Finally, telecommuting does not require that the individual use information and communication technology (ICT) when working at home, although technology (ICT) plays a significant role in enhancing telecommuting opportunities.

The May 2001 CPS supplemental survey collected information about work schedules and working at home from 51,000 working adults from approximately 47,000 households. The final CPS sample in this analysis consists of 29,147 workers who lived in an MSA and were not self-employed in their main jobs.[5] Among them

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[5] Table A1 provides information on sample construction for both the May 2001 CPS sample and the 2001 NHTS sample.

1,138 were telecommuters, accounting for 4 percent of the sample. This figure falls at the low end of the range identified in Mokhtarian et al. (2005).

Many studies of telecommuting have examined who telecommutes or why people telecommute.[6] For instance, Drucker and Khattak (2000) found in the 1995 Nationwide Personal Transportation Survey sample that *ceteris paribus*, males, older people, those with more education, those with higher incomes, parents of young children, those in rural areas and those with inferior access to transit are more likely to telecommute. They also found that one-way commute distance negatively impacts the propensity to telecommute. Popuri and Bhat (2003) and Walls et al. (2007) analyzed large data sets from New York and Southern California, respectively. They confirmed the role of the aforementioned demographic characteristics in determining telecommuting status. In addition, they found that job types and employer characteristics such as employer size and industry have significant power in explaining telecommuting adoption. However, some variables such as home location and job tenure may be affected by telecommuting status as well. Using them directly as explanatory variables yields biased model estimates in these studies.

3 Theory and Empirical Literature

The question of interest here is what effects telecommuting has on workers' journey-to-work, and, in particular, on commute length. A monocentric-city framework as described in Brueckner (2001) can be utilized to convey some simple intuition about the likely impact of telecommuting on commute length. Suppose two types of workers, commuters and telecommuters, live in a city where all employment

[6] The literature contains various definitions of telecommuting. For a comprehensive review, see Walls and Safirova (2004).

is concentrated in the central business district (CBD). Telecommuters travel to the CBD for work only part of the week while commuters go five days a week. Because telecommuters have lower commuting costs than commuters, all else equal, they bid less for homes close to the CBD and more for homes in suburban areas than commuters. In equilibrium, commuters live close to the CBD and telecommuters sort into the surrounding region with longer commutes (see Appendix A for a formal exposition).

The monocentric model, though simple and stylized, predicts that telecommuting results in a longer commute distance due to a reduction in the marginal cost of commuting. In a more realistic model that features cities with multiple employment centers (Glaeser and Kahn 2001), the result may not be so straightforward. In a polycentric city, employers who are located farther from regions where potential qualified employees live may use telecommuting as a tool in the recruitment (e.g., Prystash 1995, Guimaraes and Dallow 1999). This would attract individuals who would choose to work near their homes if they had to commute everyday. This seems particularly likely for married women who are more often the secondary earner of the family and, on average, have shorter commutes than their husbands. Thus, telecommuters could have longer commutes than non-telecommuters in a polycentric city if they choose an employer located farther from their home who offers telecommuting.

The preceding discussion suggests that the impact of telecommuting on commute length is an empirical question. The difficulty of testing the hypothesis that telecommuting increases one-way commute distance lies in that telecommuting choice is unlikely to be exogenous to commuting preference and/or behavior. If original longer commute encourages an individual to work from home when allowed, a regression of commute length on telecommuting status will overestimate the effect of telecommuting. On the contrary, telecommuters could be those who feel more pressures from traffic. They would have shorter commutes in the absence of telecommuting opportunities. This unobserved selection will lead to a downward base in the regression estimates. The existing literature has started to notice the policy significance of the question, but has not addressed it satisfactorily.

Earlier studies (e.g., Kitamura et al. 1991; Koening et al. 1996; Henderson and Mokhtarian 1996) found that telecommuting led to a large reduction in total VMTs. These studies all treat the decision to telecommute as exogenous. Among recent studies, Mokhtarian et al. (2004) analyzed retrospective data from a survey of 218 California state government employees regarding their telecommuting and commuting behavior over a ten-year period, from 1988 to 1998. The authors found that telecommuters had higher one-way commuting lengths than non-telecommuters. Again, assuming telecommuting is an exogenous choice, the study was unable to tell whether longer commuting distances encouraged telecommuting or telecommuting facilitated residential relocation farther from work. Ellen and Hempstead (2002) examined the correlation between telecommuting and city size using the work schedule supplement to the May 1997 CPS. Their results showed that telecommuters were more likely to live in large, high-density metropolitan areas. As the authors acknowledge, these results fail to shed light on a causal relationship: telecommuting opportunities were more likely to appear in information-intensive service businesses, which tend to concentrate in large, dense metropolitan areas.

4 The NHTS and an Empirical Baseline

The NHTS is a survey of the daily and long-distance travel behavior of the American public conducted periodically by the Federal Highway Administration (FHWA) since 1969. In the 2001 NHTS, 69,817 households were interviewed. The survey collected detailed information about travel of all sorts including the journey to work. A shortcoming of the NHTS data is that it does not have much information about a respondent's job, so that it is difficult to instrument for telecommuting as I do below. I instead use the NHTS to generate a conditional correlation between telecommuting and commute length, which sets a baseline for comparison with the two-sample instrumental variables estimates I obtain from the combined CPS and PUMS samples.

The sample constructed from the 2001 NHTS includes individuals who lived in a Metropolitan Statistical Areas (MSA) and had a job at the time of the survey. Unfortunately, the NHTS did not ask whether the individual was self-employed. The problem is mitigated by excluding those who always work at home or have no fixed workplace. A small portion of respondents with outlier values for commute length or speed are also removed from the sample.[7] The final sample contains 47,730 individuals from 33,326 households. I treat as telecommuters those who substitute working from home for traveling to their usual workplace once every month or more.

[7] As there is no way to identify whether outliers are due to misreporting, I employ conservative thresholds on commute length and speed in sample selection. Individuals reporting one-way commute time greater than 180 minutes, commute distance longer than 180 miles, or speed lower than 0.01 or greater than 1.5 miles per minute are removed from the sample, which results in 189 exclusions.

In this case, telecommuters constitute of 7.1 percent of the sample. This figure is higher than in the 2001 CPS because the self-employed who work in a fixed place outside the home some days and at home other days are counted as telecommuters.[8]

Table 1 reports means and standard deviations of key variables for telecommuters and non-telecommuters in the NHTS sample. It is clear that the two groups of workers differ considerably in demographic and socioeconomic characteristics. Telecommuters are, on average, more likely to be male, white, older, better educated, more likely to be married, have young children and have higher household incomes compared to non-telecommuters. Telecommuters are more concentrated in professional, managerial, or technical occupations than non-telecommuters. In terms of commuting patterns, an average telecommuter spends about 3.5 more minutes and travels an additional 2.6 miles for a one-way trip to his workplace than an average non-telecommuter. Figures 1 graph the distributions of commuters and telecommuters across groups defined by commuting distance or commuting time. The proportions of telecommuters that fall in groups with longer commutes are higher than the proportions of commuters in those groups. The last row of Table 1 shows that driving is the main travel mode for 92 percent of commuters. The proportion of workers commuting by car is 3 percentage points lower among telecommuters.

A naïve approach to examining how telecommuting impacts the journey to work is to estimate a single-equation regression model with a commuting variable (i.e.

[8] Due to data constraint, the minimum frequency requirement (one day every month) in the NHTS definition is lower than that (one day every two weeks) of the CPS. Counting the self-employed, the percentage of telecommuters in the CPS goes up to 6.2. The difference in the definitions may explain part of the remaining gap.

length or travel mode) as the dependent variable and telecommuting status, together with other relevant variables, as the explanatory variables. Table 2 reports the OLS coefficient estimates of the telecommuting dummy. Telecommuting has a large positive effect on both commute time and commute distance for married women. A married female telecommuter is estimated to travel 3 minutes or 3 miles longer to work than a married female commuter, *ceteris paribus*. The estimates for single women and men are smaller and statistically indistinguishable from zero. In terms of travel mode, telecommuters, except for single women, are less likely by 4 – 5 percentage points—to drive to work than the average commuter. However, none of these results should be interpreted as the causal effects of telecommuting as it is likely that people choose telecommuting based on how far and by which means they commute. The confounding factors would cause OLS estimates to be biased and the direction of the bias is unclear. To obtain consistent estimates of the impacts of telecommuting on the journey-to-work, we need to instrument for telecommuting choice.

The coefficient estimates for other variables indicate that commute lengths as well as probability of driving to work increase with age (at a decreasing rate), education, and household income across different population groups. Black workers commute longer than white, Hispanic and Asian workers, as is documented in the spatial mismatch literature (e.g., Kain 1968). Married men commute longer than single men. The variables have qualitatively the same effects on the probability of driving to work.

5 Empirical Strategy

5.1 Instrumental Variable

The opportunities for teleworking and telecommuting vary substantially from job to job because of the variation in the relative productivity of working from home to working on-site, which is generally determined by the need for face-to-face communication with colleagues and customers, as well as the need for team-work. The application of telecommunication technology during teleworking could alter the substitutability of teleworking for face-to-face contact. For some jobs, internet technology maintains or even increases the productivity of employees working from home, while for others, it appears less helpful. The employees in the former case are likely to have more options for teleworking and telecommuting. While a variable measuring the occupational technology penetration for teleworking may explain individual's telecommuting choice, some unobserved occupational characteristics that affect commute length might be correlated with that variable. For instance, a high school teacher uses the internet less often when she works at home than a college professor does. Furthermore, there are more high schools geographically scattered in a city than colleges. An instrumental variable that shows that a high school teacher has fewer telecommuting opportunities may also capture the difference in the geographical distributions of the two jobs if the latter is not well measured or controlled for in the model.

In the early 2000s internet services, and in particular the broadband capacity, were not evenly distributed across the country. Some studies show that internet infrastructure investment or city accessibility to the internet was biased toward larger metropolitan areas and a group of midsized urban areas (e.g. Malecki, 2002; Grubesic and O'Kelly, 2002). Consequently, the competitiveness of the broadband market varied considerably across regions. The Federal Communications Commissions (2002) shows that 40.5% of zip codes had none or one broadband line, in contrast to 27.6% of zip codes with four or more high-speed lines by June 2001. The number of broadband providers increased with population density (Grubesic and Murray, 2004), and rural and smaller metropolitan areas failed to attract significant levels of competition. The spatial variation in the internet and broadband markets could have led to spatial differences in technology options for teleworking for different occupations.

Thus, I develop an instrumental variable to measure the penetration of internet for teleworking across occupation *and* city size using the work schedule supplement to the May 2001 CPS, from which we know whether a respondent ever worked at home and what equipment they used when they were working at home. I calculate the percentage of employees for each of 270 (45 x 6) occupation-by-MSA-size combinations who ever worked at home and used the internet (hereafter referred to as internet penetration). The higher the value, the more likely a person in the occupation-by-city-size cell is to work from home and possibly telecommute. The advantage of exploiting the variation in the interaction of occupation and city size is that the effects of unmeasured occupation and urban structure attributes on commuting behavior can be purged by the introduction of occupation and city fixed effects in the model. To ensure measurement accuracy, the occupation-by-city-size cells with fewer than 50 observations are not used in the baseline analysis. This results in 179 cells covering 37 occupations and 6 MSA sizes. The cell-size weighted mean (standard deviation) of internet penetration is 0.088 (0.113). In the sensitivity analysis, I lower the cell selection criterion to 30 observations.

Figure 2 shows that internet penetration varies substantially across both occupations and city sizes. In general, white-collar workers such as professionals, teachers, and sales representatives have higher average internet penetration as well as larger variation across city sizes than blue-collar workers such as mechanics and repairmen, or transportation and production workers. College teachers and lawyers and judges have the highest teleworking internet penetration (0.5 or above), which seems reasonable since these two occupations are information intensive as well as flexible in where work is performed. Sales in finance, business and non-retail commodities have much higher percentages of internet-using teleworkers than retail sales probably because the latter require personal presence and more face-to-face interaction with customers.

It is plausible to assume that the instrumental variable is not systematically correlated with other unobservables that affect commuting behavior conditional on the occupation and city fixed effects. However, to address the concern about this assumption, I also construct a set of variables at the occupation-by-city level with the PUMS and test how robust the instrumental variable estimates are to including these variables. More detail about the occupation-by-city variables and the test is presented in the next section.

5.2 The Two-Sample Instrumental Variables (TSIV) Method

Traditionally, instrumental variables estimation is performed when the outcome variable, the potentially endogenous variable of interest and the instrumental variable exist in one data set. In addition, a large sample is generally needed for IV estimation to produce sufficient statistical power. In our case, the instrumental variable discussed above is measured for two-digit occupation by city size. It cannot be assigned to the NHTS sample because the NHTS contains little information about respondents' jobs. (A five-category variable is used to describe occupation as opposed to 45 two-digit occupations in the CPS.) To the best of my knowledge, there is no other (large) data set that contains information on commuting, telecommuting, occupation and MSA of residence.[9] Therefore, a traditional instrumental variable method is infeasible here.

Angrist and Krueger (1992) developed a two-sample instrumental variables (TSIV) technique that allows one to apply IV estimation to a joint sample with two data sets, one of which has the outcome and the instrumental variable and the other the endogenous explanatory variable and the instrument. The work schedule supplement to the May 2001 CPS collected information about respondents' working at home, occupation and MSA. The 2000 5% PUMS collected information about journey-to-work as well as occupation and MSA. Moreover, they were both intended to represent the US population within the same period and contain many of the same questions. Thus, they constitute a suitable case for the TSIV method to work.

Formally, suppose the model of interest is

$$y = X\beta + \varepsilon,$$

[9] The NLSY79, an alternative data set, provides only commuting time in the early 1990s for fewer than 10,000 workers. The information about telecommuting in the NLSY79 is limited to hours worked at home.

where y and ε are $n\times 1$ vectors and X is an $n\times k$ matrix of regressors, some of which are correlated with ε. An $n\times l$ ($l\geq k$) matrix Z is needed to consistently estimate β, where Z is not correlated with ε and $\underset{n\to\infty}{p\lim}\left(Z'X/n\right)\neq 0$. Angrist and Krueger point out that in the case when only X and Z (but not y) are observed in one data set and only y and Z (but not X) are observed in the other, β can still be consistently estimated when certain assumptions, which will be discussed in detail in the next subsection, hold for the two samples. Many researchers have since used the two-sample approach (e.g., Currie and Yelowitz 2000, Dee and Evans 2003) to circumvent the data constraint. In practice, a two-stage least squares procedure is usually adopted to produce the following estimator

$$\widehat{\beta}^{TSIV}=\left(\widehat{X}_2'\widehat{X}_2\right)^{-1}\widehat{X}_2'y_2,$$ [10]

where $\widehat{X}_2=Z_2\left(Z_1'Z_1\right)^{-1}Z_1X_1$, X_1 and Z_1 are from the first sample, and y_2 and Z_2 are from the second.

Now suppose equation (2-1) describes the structural model of commute length (or mode):

$$y_{ikc}=a+W_{ikc}B+\lambda T_{ikc}+\mu_k+\nu_c+u_{ikc} \tag{2-1}$$

where y_{ikc} is the commute time or travel mode of individual i living in MSA c with occupation k, W_{ikc} is a vector of individual specific exogenous variables, μ_k and ν_c are occupation and MSA fixed effects, and u_{ikc} is idiosyncratic disturbance. The

[10] Inoue and Solon (2005) called this estimator the two-sample two-stage least squares (TS2SLS) estimator and showed that it is different from the TSIV estimator originally proposed by Angrist and Krueger. They proved that the TS2SLS estimator is asymptotically more efficient than the TSIV estimator. That being said, I continue to label the estimator TSIV to distinguish it from the one-sample IV approach.

potentially endogenous variable, T_{ikc}, is an indicator for telecommuting. The parameter of interest, λ, measures the causal impact of telecommuting on commute length or travel mode.

The first stage in calculating the TSIV estimate of λ is to estimate a model of telecommuting adoption as described by equation (2-2),

$$T_{1ikc} = a_1 + W_{1ikc}B_1 + \lambda_1 Z_{1ks} + \mu_{1k} + \nu_{1c} + u_{1ikc},\ \ i = 1, \ldots, n_1 \tag{2-2}$$

where the subscript 1 denotes the CPS sample, n_1 is the sample size in the CPS, and Z_{ks} is the instrumental variable measured at occupation by MSA size level (s). The parameters estimates are applied to the second sample, i.e. the PUMS sample, to predict telecommuting status, $\widehat{T}_{2ikc}$. In the second stage, the TSIV estimate of λ is generated by regressing the outcome variables in the PUMS, y_{2ikc}, on the predicted telecommuting status, $\widehat{T}_{2ikc}$ and other covariates. In an exactly identified case such as ours, we can alternatively fit a reduced-form equation, i.e. equation (2-3), using the PUMS sample,

$$y_{2ikc} = a_2 + W_{2ikc}B_2 + \lambda_2 Z_{2ks} + \mu_{2k} + \nu_{2c} + u_{2ikc},\ \ i = 1, \ldots, n_2 \tag{2-3}$$

where subscript 2 denotes the PUMS sample and n_2 is the sample size of the PUMS. The TSIV estimate is just the ratio between the reduced-form and first-stage coefficients before Z_{ks}, i.e.

$$\hat{\lambda}^{TSIV} = \frac{\hat{\lambda}_2}{\hat{\lambda}_1}.$$

Standard errors of the TSIV estimator can be computed using a linear Taylor series approximation assuming zero covariance between the first-stage and reduced-form estimators. That is

$$\hat{\sigma}_{TSIV}^2 = \frac{\hat{\lambda}_2^2}{\hat{\lambda}_1^2}\left(\frac{\hat{\sigma}_1^2}{\hat{\lambda}_1^2} + \frac{\hat{\sigma}_2^2}{\hat{\lambda}_2^2}\right) \qquad (2\text{-}4)$$

where $\hat{\sigma}_1$ and $\hat{\sigma}_2$ are estimated standard errors of $\hat{\lambda}_1$ and $\hat{\lambda}_2$, respectively.[11]

5.3 CPS and PUMS Samples

In addition to assumptions underlying the traditional IV model, the TSIV approach imposes some conditions on the joint sample. The key one is that the two data sets must represent the same population. It is plausible to argue that these conditions hold for the samples constructed from the CPS and the PUMS. The CPS is administered by the Bureau of the Census for the Bureau of Labor Statistics. The former is also in charge of implementing the decennial census of the US, from which the PUMS was created. Both the CPS and the PUMS collected a rich set of information from US households on individuals' demographic characteristics, labor force experience, household attributes and economic status. In addition to the similarity in content, the phrasing of questions and coding of potential responses are similar across the CPS and the PUMS. While the CPS and PUMS are both intended to be representative of the US population, the PUMS includes institutionalized individuals, who are excluded from the CPS. I remove these observations from the

[11] Note that with this approximation formula the *t*-statistic of the TSIV estimates is the following function of the *t*-statistics of the first-stage and reduced-form estimates: $t_{TSIV}^2 = \frac{t_1^2 t_2^2}{t_1^2 + t_2^2}$. When t_1, the first-stage *t*-statistic outweighs t_2, t_{TSIV} approaches t_2.

PUMS in constructing the joint sample. Moreover, every variable in the sample is ensured to have the same support across the two sources. For instance, only workers who are 16 years old or above, live in an MSA and are not self-employed on the main job are retained in my data. MSAs that appear in just one data set are removed. The final data includes 234 common MSAs.

Nevertheless, potential mismatches between the CPS and the PUMS might exist due to the differences in sampling design, response rates and survey times. The CPS selects households by primary sampling units (PSUs) based on the 1990 Census while the PUMS draws households with sampling rates varying with the housing density of census blocks or tracts.[12] Second, the Census spent tremendous effort to induce people to fill out the survey forms, which led to higher response rates in the Census than the CPS. Finally, the CPS data were collected in May 2001 roughly one year after the 2000 Census was conducted. A visual comparison of the weighted means[13] of the CPS and the PUMS samples does not suggest significant differences for most variables between the samples. However, *t*-tests reject the mean equality for several variables across the two samples.[14]

Table 3 presents descriptive statistics for telecommuters and non-telecommuters in the CPS sample. Telecommuters are 3 – 4 years older than commuters on average,

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[12] See http://usa.ipums.org/usa/chapter2/chapter2.shtml for a detailed explanation.

[13] Sample weights contained in the CPS and PUMS are applied in calculating summary statistics and estimation to adjust the over-sampling in each survey.

[14] In the notation of section 5.2, the condition on the joint sample can be formally written as

$$\operatorname*{plim}_{n_1\to\infty}\left(Z_1'X_1/n_1\right)=\operatorname*{plim}_{n_2\to\infty}\left(Z_2'X_2/n_2\right)=\Sigma_{ZX}\,.$$

It requires that the first and second moments of explanatory variables including the instrumental variable of the two samples converge to the same matrix. It can be tested for the variables that are observed in both samples. A *t*-test on the means just examines the first moment and is likely to reject the null given large sample size. With increasing applications of the TSIV method, formal ways to test the assumption and to evaluate the potential bias resulting from mismatch of the two samples are probably desirable.

and disproportionately white and better educated. They are more likely to be married and live in smaller households, with higher annual incomes. In terms of job types, telecommuters are concentrated in occupations such as executives, administrators, managers, math and computer scientists, teachers of all levels, lawyers and judges, and sales representatives in finance and business services—workers who are generally in the upper levels of the job hierarchy. White-collar workers in the service sector and blue-collar workers have fewer opportunities to telecommute. Finally, a higher proportion of telecommuters than non-telecommuters live in large MSAs with populations over one million. As in Table 1, Table 3 shows that telecommuters and non-telecommuters differ in many observed ways. It is therefore likely that they also differ in unobserved variables that are correlated with commuting behavior.

In the PUMS, commute length is recorded in minutes and measures how long it usually took the respondent to get from home to work during the past week. White (1988a) argues that time is a better measure of commuting costs than distance because time is the scarce resource that people economize. Moreover, Table 2Table shows that the same set of variables explains more variation in commute time than commute distance, This suggests that the noise associated with distance is larger than with time: A commuter can estimate commuting time more accurately than distance. The translation of the impact of telecommuting on commute time into an impact on commute distance is considered below.

In the PUMS, 1.7 percent of the sample or over 60,000 respondents have travel times that are top-coded at 99 minutes. Exploiting the properties of the Pareto distribution, I replace the top-coded values with an estimate of the conditional expectation for top-coded values. The procedure is described in Appendix B, which suggests a range for the imputed values of 120 to 165 minutes. I use the lower bound, 120 minutes, in the benchmark analysis. Since the likelihood of being top-coded is positively correlated with telecommuting adoption, using the lower bound value works against finding a positive effect of telecommuting. I check whether different imputed values affect the results in the sensitivity analysis. The weighted average commute times in the PUMS are 24.2, 24.7 and 27.5 minutes for married women, single women and men, respectively. These figures are slightly higher than in the NHTS sample, which are 22.1, 22.9 and 25.2, respectively. In the PUMS, a higher share (93.3%) of married women drives to work than single women (85.1%) and men (89.8%). Similar patterns are observed in the NHTS sample, for which the shares are 94.1%, 87.7%, and 91.7%, respectively.

6 The First-Stage Estimates

In the first stage, I estimate a linear probability model of telecommuting adoption (equation (2-2)). The dependent variable is a binary indicator equal to one if the worker is telecommuting. In the baseline model, the explanatory variables include age, age squared, gender, race, educational achievement, number of household members, presence of children 5 years of age or younger, children between 6 and 15 years of age, spouse (for the male sample only), annual household income, and the occupation-by-city-size internet penetration measure. Industry and job class variables are not included in the model because they are individual choices that are likely to be correlated with home location, work location or commute length. Neither the wage, housing price, or travel mode and time is used as an explanatory variable. All of these are chosen simultaneously with commute length and, therefore, are endogenous. Fixed effects for MSA-of-residence and 2-digit occupation category are controlled for, assuming people do not sort into a city and 2-digit occupation based on their preferences for commute length or telecommuting.

The model is estimated for married women, single women and men separately using individual weights provided by the CPS. Results are reported in Table 4. In general, the estimates reflect the differences between telecommuters and commuters in Table 3. People who are older, white, possess a college or advanced degree, have children and come from affluent households are more likely to telecommute. Less obvious from the descriptive statistics is that black employees have a higher probability of working at home than other groups, although a lower probability than whites. Being married does not seem to play a role in the telecommuting decisions for male employees. All else equal, telecommuting is significantly more popular among professionals and sales representatives in finance and business services, but less popular among engineers and supervisors. Surprisingly, blue-collar workers are not less likely to telecommute than white collar workers, conditional on demographic and economic covariates. This may be because people with less education are offered more telecommuting opportunities when working in blue-collar jobs than in white-collar jobs.

Several variables have differing influences on telecommuting adoption across the samples. Race plays an important role in telecommuting for married women but not for single women. In contrast, household size and income are more important for the latter than for the former. The likelihood of telecommuting increases with age at a decreasing rate for women workers. This pattern is much weaker and statistically insignificant for men. A male employee with a graduate degree has a substantially larger propensity to telecommute than one with a college degree, but this is not the case for a female employee. Men tend to work at home if there are older children but not younger children in the household. The reverse is true for married women – suggesting that married women may use telecommuting as a way to combine work and childcare.

The coefficients on the instrumental variables are of paramount importance and vary substantially across samples. In the case of married women, a 10 percentage point increase in occupation/MSA internet penetration causes the probability of telecommuting to rise by 5.4 percentage points once 2-digit occupation and MSA fixed effects are controlled for. This effect is statistically significant at the1% level. On the contrary, the estimate for single women is smaller (0.143) and statistically insignificant, suggesting the instrumental variable has little explanatory power for single women employees. For male employees, a 10 percentage point increase in internet penetration increases the probability of telecommuting by 2.9 percentage points, an effect that is significant at the 5% level.

One critical assumption underlying the IV approach is that teleworking technology penetration is not correlated with any unobservable that influences commute length or mode. There might be concerns that the instrumental variable is correlated with occupation-specific local labor market conditions. For instance, the urban economics literature hypothesizes that individuals are forward looking when they choose home location and commute length. They take into account labor market dynamics and potential moving costs. Specifically, Crane (1996) predicts a shorter commute for persons with lower probability of changing jobs within the local labor market. Likewise, van Ommeren et al. (1997) argue that commuting distance is decreasing in the arrival rates of job offers and increasing in moving costs.

One way to deal with this concern is to control in the model for occupation-by-city attributes. Lacking clear theory informing what those attributes should be, I construct a rich set of covariates using the PUMS data. I calculate the fraction of employees within each 2-digit occupation and MSA combination who are: male, white, black, have a high school degree, some college experience, a college degree, an advanced degree (omitting high school dropouts), in the transportation and communication industries, in trade, in finance, in services, in public administration (omitting the manufacturing and construction industries), working for private for profit employers, and working for private non-profit employers (omitting government). I also compute the labor market share, median hourly wage, and difference between the 75th percentile wage and the 25th percentile wage of each occupation by MSA. Finally, using the CPS sample, I calculate the fraction of employees for each 2-digit occupation and MSA size combination who have flexible work hours.

Even columns in Table 4 report estimation results for the model with inclusion of these occupation-city specific covariates. The coefficients of demographic and household variables do not change much, although some occupation fixed effects vary. This suggests that the constructed covariates pick up part of the variation in telecommuting explained by occupation. The coefficient on internet penetration declines slightly to 0.48 for married women while statistical significance is maintained at the 1% level. The coefficient for men is unchanged up to two decimal places. These results indicate that the instrumental variable is likely to be orthogonal to the local labor market conditions described by those covariates.

7 Reduced-Form and TSIV Estimates

7.1 Reduced-Form Estimates

Equation (2-3) is estimated only for married women and men since the instrumental variable is not statistically significant for single women. The exogenous explanatory variables are the same as in the first-stage except that they are from the PUMS sample. Results are reported in Table 5. In the baseline model, commute length increases with age at a decreasing rate for both women and men. Race makes a substantial difference in commute length, which may reflect residential segregation and employment separation. Black male workers on average spend 2 more minutes on the road than white and other workers and black females travel 4 minutes longer than white females. Regardless of gender, college graduates and those from high-income households live farther from their workplace than employees without a college degree and workers from low income households. Married men travel 1 minute longer to work than single men. When there are younger children in the household, both married women and men travel longer to work, while the presence of older children has the opposite, but smaller, effect for women. Commute time increases with the number of household members for men and decreases for married women. Overall, the results are consistent with those from the NHTS and largely agree with those in White (1986). Commute length varies significantly across jobs even conditioning on factors like age, race, and education. One possible reason is the variation in geographic concentrations of different occupations. For example, school teachers have short commutes because schools are scattered throughout a city.

The instrumental variable shows large positive impacts on married women's commute lengths but not on men's commute lengths. In the baseline model without controlling for occupation-MSA covariates, i.e., Columns 1 and 3, a 10 percentage point increase in the proportion of employees of each 2-digit occupation and MSA size combination who ever use internet when working at home leads to 0.60 minute longer commuting trip for married women. The estimate is statistically significant. In contrast, the coefficient estimate of the internet penetration for male workers is 0.13 minutes and statistical insignificant.

When the occupation-by-city covariates are controlled for in the model, few changes occur in the coefficients of the demographic and household variables. However, a number of occupation fixed effects vary dramatically. This suggests the importance of heterogeneity in local markets for different occupations in determining commute length. The coefficients of the occupation-MSA covariates imply that conditional on individual characteristics, commute length increases if the person works in an occupation that has more human capital, is concentrated in finance and services industries, is more represented in the private for profit sector and has a larger labor market share. The last result seems to be consistent with Crane’s theory that a person values commuting distance less if more potential employers are available.

The effect of internet penetration on commuting length declines slightly and retains statistical significance for married female workers. Now, a 10 percentage point increases in internet penetration lead to an additional 0.46 minutes in commute time for married women. The estimate for male workers is less than 0.2 minutes and statistically insignificant. The results, consistent with those without occupation-by-city covariates, suggest that the instrumental variable is unlikely to pick up the occupation-city specific attributes as confounding factors.

7.2 TSIV Estimates of the Effects on Commute Length

First-stage estimates indicate that the internet penetration instrumental variable has statistically significant and positive impacts on the telecommuting status of married women and men in the 2001 May CPS. The reduced-form estimates indicate that the instrumental variable has a substantial positive effect on one-way commute time of married women but little effect for male employees in the 2000 PUMS. The TSIV procedure ties these two sets of results together to generate consistent estimates of the causal effects of telecommuting on commute length.

Table 6a presents the TSIV estimates calculated as the ratios of reduced-form estimates to the first-stage estimates of the instrumental variable. In the exactly identified case, it yields the same estimates as the two-stage least square estimation in the two sample case (TS2SLS). The standard errors of the TSIV estimates are computed using equation (2-4). The TSIV estimates suggest that telecommuting has a substantial positive impact on married women's commute lengths. All else equal, working at home at least one day every two weeks, on average, causes a married women employee to commute 9 – 11 minutes longer than if she commutes every day. The impact for male employees is smaller in magnitude (around 5 minutes) and statistically indistinguishable from zero. In comparison with OLS estimates, the TSIV estimates yield qualitatively similar results. However, OLS results underestimate the effect of telecommuting for married women, which is consistent with the fact that married women usually have short commutes if they do not telecommute.

7.3 Effects of Telecommuting on Commute Mode

OLS analysis of the NHTS data shows that male and married female telecommuters are less likely to drive to work than non-telecommuters. It is difficult to find a compelling reason why telecommuting leads people to forego driving to work. The OLS estimates are susceptible to an omitted variable bias that fails to account for sorting of women who take public transit to work into telecommuting. Moreover, driving usually is faster than taking public transit or any other travel mode.[15] If telecommuting does cause a worker to commute by a mode other than driving, the lengthened commute time might be a result of choosing a slower travel mode rather than an increase in commute distance. Therefore, it is important to identify the true effect of telecommuting on commute mode.

I apply the same TSIV procedure to the travel mode variable available in the PUMS sample. Using the same argument that internet penetration is unlikely to affect travel mode choice directly, TSIV produces consistent estimates of the effects of telecommuting on travel mode choice. Table 6b reports both reduced-form and TSIV estimates for travel mode. In the baseline model, the TSIV estimates are small, positive and without statistical significance for both married women and men. When the occupation-by-city covariates are added, the estimate for married women is almost zero while the estimate for men becomes negative with a large standard error.

[15] The average speeds for commuting by driving, by rail, by bus, and by bicycle in the NHTS are 0.53, 0.36, 0.28, and 0.23 miles per minute, respectively.

Overall, the TSIV point estimates do not support the OLS results that telecommuting reduces a married woman's probability of driving to work. The negative OLS estimates could result from the fact that employees who commute by public transit also prefer to telecommute. However, the TSIV estimates are not sufficiently precise to let us draw definite conclusions about the effect.

7.4 Sensitivity Analysis

I examine the sensitivity of the above results to different sample restrictions and alternative imputed values for the top-coded commute times. Tables 7a and 7b report the estimates for the commute time and travel mode models, respectively. In Panel A of each table, the samples are extended to include the occupation-MSA size cells that contain 30 or more CPS observations, which results in 216 cells covering 38 2-digit occupations and 6 MSA sizes. In the first stage, the instrumental variable has a smaller effect for married women while the coefficient for men does not change much as compared to the case with cells containing over 50 observations. It continues to have a large, statistically significant reduced-form effect on married women's commute time and little effect on men's commute time. The TSIV estimates show that telecommuting increases married women's commute time by 13 minutes though they lack enough statistical power in the case with job-by-city covariates included. The effect of telecommuting among male employees falls to 3 and 4 minutes, and the *t*-statistics are less than 1. As far as travel mode is concerned, telecommuting shows some positive effects for both married women and men, but again the estimates are not distinguishable from zero. These results are highly consistent with the baseline case with cells larger than 50 observations.

Telecommuting is often thought of as a choice for office workers only. Programs and policies that aim at promoting telecommuting usually target these occupations rather than the entire working population. Therefore, it may be of interest to examine the effects of telecommuting on commuting behavior for office workers. One way to define office workers is to narrow the sample down to the 2-digit occupations coded 1 through 26. Included in this group are managerial, professional specialty, technical, sales, and administrative support occupations. 2-digit occupation codes greater than 26, including service, precision production, craft, repair, farming, forestry and fishing occupations and operators, fabricators and laborers, are excluded. Panels B of Tables 7a and 7b present the estimates for the sample of office workers. The instrumental variable affects only the telecommuting propensity of married women. Telecommuting is estimated to lengthen the one-way commute time of married women by 8 - 9 minutes, which is statistically significant at the 10% level. Again, telecommuting has a positive but statistically insignificant effect on married women's commute mode, contrary to the OLS estimates. In sum, estimates with different sample restrictions demonstrate that the effects of telecommuting on commuting show stability and a certain degree of homogeneity across occupations. Panel C of Table 7a shows that replacing the top-coded commute time by 165 minutes instead of 120 minutes has no impact on the effects of telecommuting on commute time.

8 Discussion

The TSIV estimates of the effects of telecommuting on commute time for married women equal 9 to 12 minutes, which are 3 to 4 times the OLS estimates from the NHTS. The results are plausible in that married women have shorter commutes on average. The OLS analysis tends to underestimate the effects of telecommuting in this case. The magnitude of the adjustment in the commute made by married women appear reasonable given that the average commute time for married women in the PUMS is 24.2 minutes with a standard deviation of 19. TSIV estimates suggest that telecommuting increases commute time by about half of a standard deviation.

TSIV estimation could be biased if the internet penetration measured by occupation crossed with MSA size is correlated with some unobservables that impact individual commute lengths. The concern may be less serious as the models control for a rich set of occupation-by-city specific covariates as well as occupation and city fixed effects. Another potential source of bias is that the teleworking technology penetration is measured with 2001 CPS data. When internet access expanded rapidly to a wider population and more regions in the early 2000s, the variation across occupation and cities declined quickly with time. Therefore, the impact of internet penetration on telecommuting adoption estimated using 2001 data may underestimate the impact in year 2000 when the PUMS were collected, which would result in an overestimation of the TSIV coefficients.

I am interested in translating the effects of telecommuting on commute time into the effects on commute distance. I use the NHTS data to estimate a relationship between commute time and distance for people driving to work. Table 8 shows the coefficients of models that project commute time onto commute distance and distance squared.[16] Commute time is a concave function of distance with an intercept greater than zero, which suggests a positive fixed cost and an increasing marginal speed. The

[16] Higher order polynomials were tried. They produce very bad predictions for distances on the high end. Moreover, the predictions for the mid-range values do not differ with and without the higher order terms.

relationship between commute time and distance varies by sex, with women having greater concavity. Using these estimates, we can recover the approximate distance from travel time. For instance, suppose a woman drove 24 minutes to work before choosing to telecommute. Applying the projection estimates implies that on average her commute distance was 13 miles. If her one-way commute time increases to 33 minutes after telecommuting, the one-way commute time increases to 20.5 miles, a 7.5 miles increase. If she works from home 2 days a week (the national average for telecommuting women is 2.2 days per week), the total weekly commutes are 198 minutes or 123 miles, representing 17 percent and 5.5 percent declines relative to the before-telecommuting commute times and commute miles, respectively.

9 Conclusion

Telecommuting has been promoted as a means to deal with congestion and automobile emissions by researchers and public policy makers. However, there are concerns that telecommuting workers will make a longer commute in response to the lower commute frequency. Naïve (OLS) estimates based on the NHTS show that a married woman commutes 3 minutes or 3 miles longer if she telecommutes. The NHTS estimates also show that telecommuters except single women are less likely to drive to work than non-telecommuters. However, these estimates could be biased because telecommuting is not randomly assigned among workers. Furthermore, theory cannot predict the direction of the bias.

By applying two-sample instrumental variables technique to the CPS and PUMS samples, I find that telecommuting causes married women employees’ commuting trips to increase by 9 to 12 minutes. The effect for male workers is also positive, but smaller and not precisely estimated. For single women, the instrumental variable does not have enough power to explain telecommuting choice. In addition, TSIV estimates show a small, positive effect of telecommuting on the probability of commuting by car for married women. Although lacking statistical power, this does not agree with the negative relationship between telecommuting and driving to work found in the OLS analysis. Given the sizable “rebound” effect on one-way commute time found among married women, the total commute miles traveled by an average married women worker are unlikely to decline in proportion to telecommuting frequency.

Unfortunately, the instrumental variable developed in this paper does not have enough information to let us estimate the effects of telecommuting for men and single women. This needs to be explored in future research. Moreover, to understand whether telecommuters adjust their commute distance by changing residential location or employment location is important for both research and policy purposes and should also be examined.

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Figure 1. Distributions of Telecommuters and Commuters by Commute Time and Distance

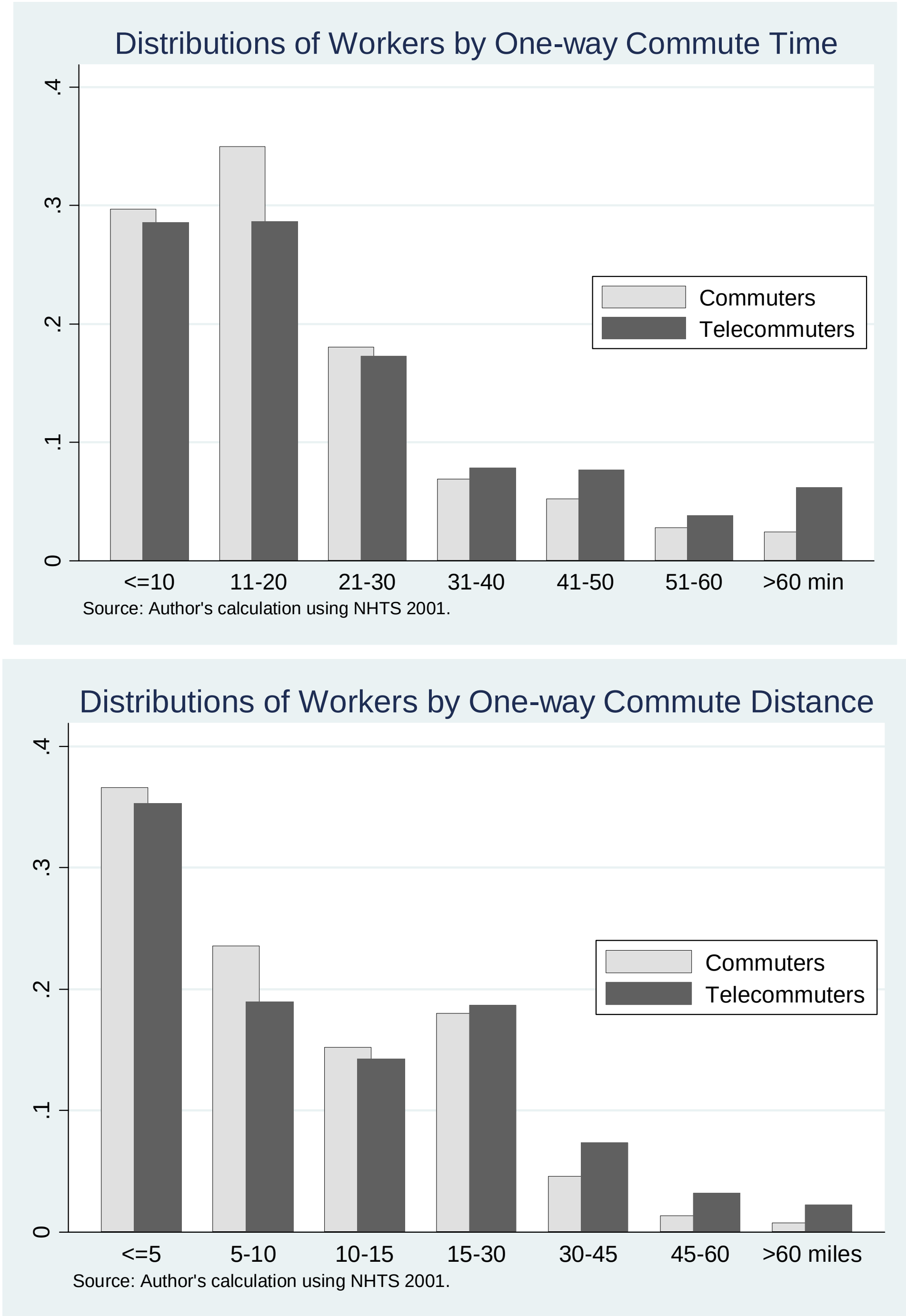
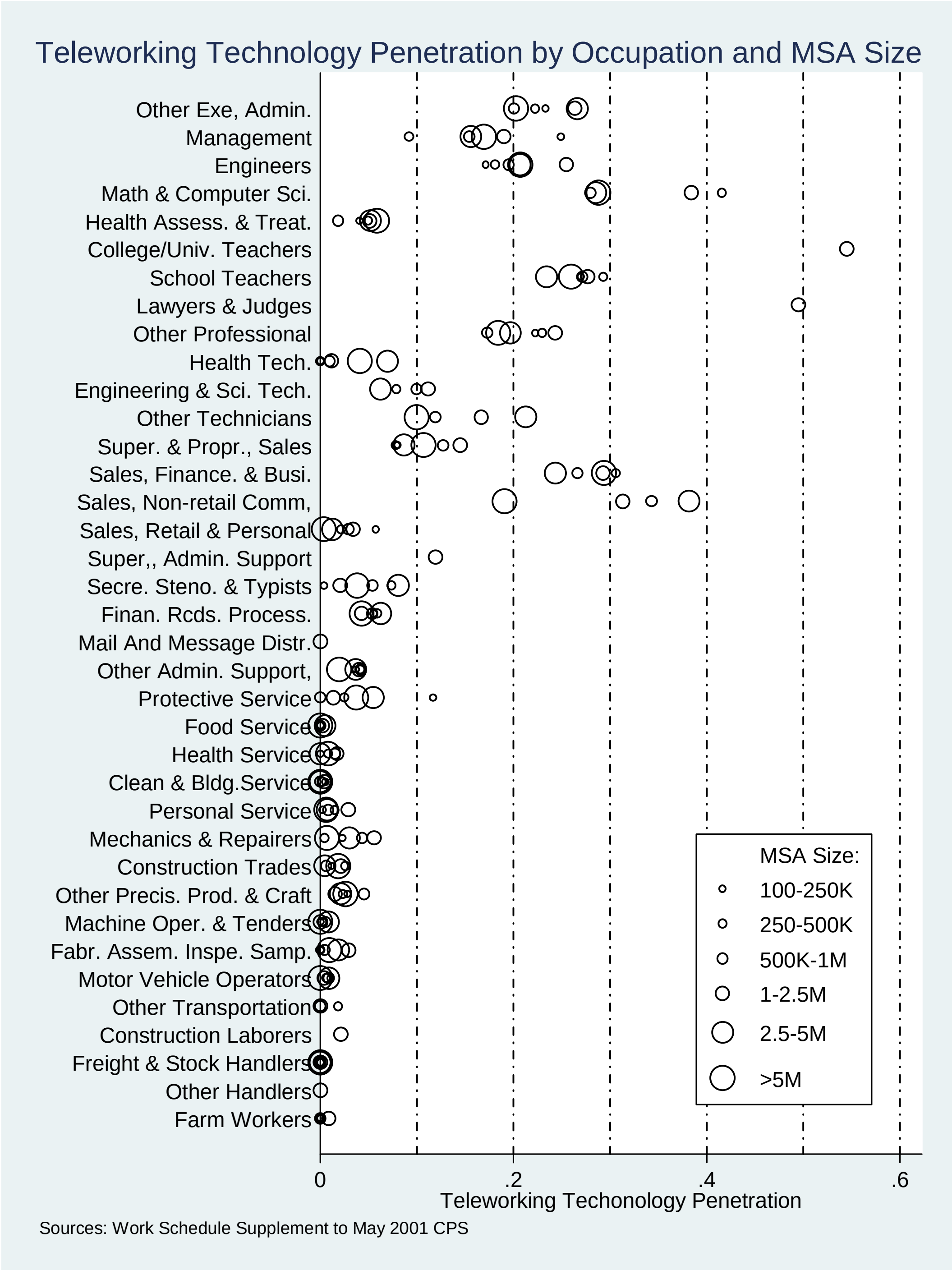


Figure 2. Internet Penetration by 2-Digit Occupation and MSA Size (2001 CPS)



Note: Internet penetration is calculated as the weighted percentage of employees who ever work at home and use the internet within each occupation-by-MSA-size cell using data from the Work Schedule Supplement to the May 2001 CPS.

Table 1. Descriptive Statistics of NHTS Sample

	Non-telecommuters		Telecommuters	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Raw N	44556		3174	
Age	39.205	12.370	42.250	11.243
Male	0.541	0.498	0.599	0.490
White	0.708	0.455	0.807	0.395
Black	0.123	0.329	0.060	0.238
Asian	0.029	0.168	0.044	0.206
Hispanic	0.110	0.313	0.056	0.231
High School Degree	0.290	0.454	0.111	0.314
Some College	0.303	0.460	0.252	0.434
College Degree	0.216	0.411	0.369	0.483
Graduate Degree	0.115	0.319	0.248	0.432
Spouse	0.608	0.488	0.664	0.472
Child Age 0 – 5 in HH	0.211	0.408	0.225	0.418
Child Age 6 – 15 in HH	0.310	0.463	0.312	0.464
Household Size	3.152	1.441	2.990	1.364
HH Income $40 – 70K	0.322	0.467	0.233	0.423
HH Income $70 – 100K	0.191	0.393	0.256	0.437
HH Income > $100K	0.152	0.359	0.343	0.475
Sales or Services	0.266	0.442	0.236	0.425
Clerical or Administrative Support	0.136	0.342	0.059	0.236
Manufacturing, Construction, Maintenance, or Framing	0.180	0.384	0.061	0.239
Professional, Managerial, or Technical	0.417	0.493	0.644	0.479
Time to Work	23.688	17.889	27.167	22.362
Distance to Work	12.628	12.800	15.238	16.194
Drive to Work	0.917	0.276	0.884	0.321

Note: Sample is constructed from the 2001 NHTS including workers who live in an MSA, have an outside-home fixed workplace, and have one-way commute distance less than 180 miles, commute time less than 180 minutes and commute speed less than 1.5 miles per minute and greater than 0.01 miles per minute. Observations with missing values for any of the listed variables are also dropped. Means and standard deviations are calculated using the weights from the NHTS.

Table 2. OLS Estimates of the "Effect" of Telecommuting on Commute Lengths and Travel Mode, 2001 NHTS

	Married Women	Single Women	Men
Telecommuting	(1)	(2)	(3)
	A. COMMUTE TIME (MINUTES)		
Coefficient	2.904**	0.452	1.652
Standard Error	(1.225)	(1.410)	(1.040)
R-sq	0.11	0.12	0.08
	B. COMMUTE DISTANCE (MILES)		
Coefficient	3.124***	1.063	1.144
Standard Error	(0.968)	(1.010)	(0.699)
R-sq	0.09	0.09	0.05
	C. DRIVE TO WORK		
Coefficient	-0.043**	0.013	-0.051***
Standard Error	(0.019)	(0.025)	(0.014)
R-sq	0.11	0.17	0.13
# Observations	14176	8939	24615

Note: The sample is the same as in Table 1. All models include age, age squared, race, education, household composition, annual household income, and job category and MSA fixed effects. Heteroscedastic-robust standard errors without clustering are in parentheses. * indicates significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 3. Descriptive Statistics of CPS Sample by Gender and Telecommuting Status

	Women				Men			
	Non-telecommuters		Telecommuters		Non-telecommuters		Telecommuters	
Variables	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
Raw N	13528		594		14481		544	
Age	38.678	12.806	41.663	10.829	38.437	12.614	43.020	11.367
White	0.795	0.404	0.886	0.318	0.833	0.373	0.921	0.271
Black	0.148	0.355	0.081	0.273	0.111	0.314	0.045	0.208
High School Degree	0.285	0.452	0.139	0.346	0.283	0.450	0.096	0.295
Some College	0.314	0.464	0.227	0.419	0.272	0.445	0.175	0.381
College Degree	0.204	0.403	0.399	0.490	0.201	0.401	0.416	0.493
Graduate Degree	0.086	0.281	0.202	0.402	0.095	0.293	0.300	0.459
Spouse Present	0.501	0.500	0.642	0.480	0.577	0.494	0.730	0.444
With Child 0 – 5 in HH.	0.194	0.395	0.222	0.416	0.221	0.415	0.196	0.397
With Child 6 – 15 in HH.	0.327	0.469	0.338	0.474	0.314	0.464	0.320	0.467
Household Size	3.076	1.495	3.029	1.444	3.236	1.592	2.924	1.426
Annual Family Income < $40K	0.364	0.481	0.163	0.369	0.320	0.467	0.087	0.282
Annual Family Income $40 – 75K	0.337	0.473	0.310	0.463	0.355	0.479	0.245	0.430
Annual Family Income > $75K	0.299	0.458	0.527	0.500	0.325	0.469	0.669	0.471
<u>2-digit Occupation</u>								
01 Public Administrators and Officials	0.000	0.016	0	0	0.001	0.025	0	0
02 Other Executive, Administrators, and Managers	0.099	0.299	0.165	0.371	0.120	0.324	0.252	0.435
03 Management Related Occupations	0.053	0.224	0.077	0.267	0.032	0.175	0.063	0.244
04 Engineers	0.004	0.065	0.003	0.057	0.035	0.184	0.046	0.210
05 Math. and Computer Scientists	0.013	0.111	0.038	0.192	0.025	0.156	0.051	0.221
06 Natural Scientists	0.003	0.058	0.010	0.100	0.005	0.069	0.006	0.077
07 Health Diagnosing Occupations	0.005	0.067	0.004	0.059	0.007	0.082	0.010	0.102
08 Health Assessment and Treating	0.049	0.216	0.026	0.160	0.007	0.083	0	0
09 College and University Teachers	0.007	0.082	0.045	0.208	0.007	0.085	0.057	0.232
10 Other Teachers	0.065	0.246	0.152	0.359	0.021	0.143	0.039	0.194
11 Lawyers and Judges	0.004	0.066	0.010	0.097	0.007	0.082	0.032	0.177
12 Other Professional Specialty	0.042	0.200	0.097	0.296	0.032	0.177	0.110	0.313
13 Health Technologists and Technicians	0.025	0.155	0.007	0.084	0.004	0.060	0	0
14 Engineering and Science Technicians	0.007	0.084	0.003	0.052	0.015	0.123	0.009	0.093
15 Other Technicians	0.010	0.100	0.014	0.116	0.015	0.121	0.027	0.162
16 Sales Supervisors and Proprietors	0.027	0.162	0.024	0.154	0.033	0.180	0.032	0.176
17 Sales Representatives, Finance and Business Service	0.018	0.132	0.055	0.229	0.018	0.131	0.089	0.285
18 Sales Representatives, Commodities except Retail	0.006	0.075	0.017	0.129	0.018	0.131	0.073	0.261
19 Sales Workers, Retail and Personal Services	0.067	0.249	0.026	0.159	0.036	0.186	0.020	0.139
20 Sales Related Occupations	0.001	0.030	0	0	0.000	0.021	0	0
21Supervisors, Administrative Support	0.010	0.099	0.001	0.038	0.004	0.064	0.003	0.055
22 Computer Equipment Operators	0.004	0.060	0.001	0.036	0.003	0.054	0	0
23 Secretaries, Stenographers, and	0.042	0.201	0.040	0.197	0.001	0.031	0.003	0.055

Typists								
24 Financial Records Processing	0.028	0.164	0.030	0.170	0.003	0.056	0.003	0.057
25 Mail and Message Distributing	0.005	0.073	0	0	0.010	0.099	0.002	0.044
26 Other Administrative Support Occupations, including Clerical	0.153	0.360	0.078	0.269	0.046	0.209	0.009	0.094
27 Private Household Service	0.001	0.025	0.004	0.061	0	0	0	0
28 Protective Service Occupations	0.009	0.093	0.002	0.044	0.031	0.172	0.004	0.066
29 Food Service Occupations	0.058	0.234	0	0	0.044	0.206	0	0
30 Health Service Occupations	0.036	0.186	0.007	0.086	0.004	0.064	0.003	0.056
31 Cleaning and Building Service	0.022	0.145	0	0	0.025	0.156	0	0
32 Personal Service	0.041	0.199	0.046	0.210	0.009	0.093	0.002	0.041
33 Mechanics and Repairs	0.004	0.061	0.003	0.052	0.061	0.240	0.024	0.153
34 Construction Trades	0.002	0.048	0	0	0.071	0.257	0.007	0.082
35Other Precision Production	0.012	0.111	0.004	0.066	0.040	0.195	0.003	0.050
36 Machine Operators and Tenders	0.024	0.153	0.001	0.023	0.039	0.194	0.004	0.065
37 Fabricators, Assemblers, Inspectors, and Samplers	0.016	0.124	0.007	0.083	0.025	0.155	0.001	0.036
38 Motor Vehicle Operators	0.008	0.089	0	0	0.052	0.222	0	0
39 Other Transportation and Material Moving	0.001	0.027	0	0	0.018	0.131	0	0
40 Construction Laborer	0.000	0.015	0	0	0.013	0.114	0.005	0.069
41 Freight, Stock and Material Handlers	0.012	0.107	0.003	0.057	0.034	0.182	0	0
42 Other Handlers, Equipment Cleaners, and Laborers	0.005	0.067	0	0	0.011	0.102	0.001	0.036
43 Farm Operators and Managers	0.000	0.018	0	0	0.000	0.021	0.004	0.060
44 Farm Related Workers	0.006	0.079	0	0	0.021	0.142	0.003	0.056
45 Forestry and Fishing Occupations	0.000	0.008	0	0	0.001	0.022	0.003	0.051
MSA w/ Population 100k – 250k	0.089	0.284	0.062	0.241	0.084	0.278	0.076	0.266
MSA w/ Population 250k – 500k	0.140	0.347	0.115	0.319	0.134	0.341	0.094	0.291
MSA w/ Population 500k – 1m	0.166	0.372	0.139	0.346	0.156	0.363	0.111	0.314
MSA w/ Population 1m – 2.5m	0.306	0.461	0.339	0.474	0.316	0.465	0.390	0.488
MSA w/ Population 2.5m – 5m	0.168	0.374	0.195	0.397	0.176	0.380	0.191	0.393
MSA w/ Population 5m+	0.131	0.338	0.150	0.357	0.134	0.341	0.138	0.346

Note: Sample is constructed from the May 2001 CPS including workers who live in an MSA and are not self-employed on the main job. Observations with missing values for any of the listed variables are also dropped. Means and standard deviations are calculated using the weights from the CPS.

Table 4. First-Stage Estimates of Telecommuting Models, May 2001 CPS

	Married Women		Single Women		Men	
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.004**	0.004**	0.002**	0.002**	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	-0.000*	-0.000*	-0.000*	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.044***	0.042***	0.014	0.013	0.026***	0.026***
	(0.009)	(0.008)	(0.010)	(0.010)	(0.006)	(0.006)
Black	0.023*	0.020	0.010	0.010	0.019***	0.019***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.007)	(0.007)
High Scholl Degree	-0.013	-0.014	-0.005	-0.005	0.001	0
	(0.011)	(0.011)	(0.004)	(0.003)	(0.003)	(0.003)
Some College	-0.008	-0.010	0.001	0.001	-0	-0.001
	(0.012)	(0.012)	(0.005)	(0.005)	(0.004)	(0.004)
College Degree	0.034**	0.033**	0.026***	0.027***	0.025***	0.024***
	(0.014)	(0.014)	(0.008)	(0.008)	(0.008)	(0.008)
Graduate Degree	0.023	0.021	0.009	0.010	0.035***	0.035***
	(0.019)	(0.019)	(0.015)	(0.015)	(0.011)	(0.011)
Spouse					0.001	0.001
					(0.005)	(0.005)
With Child 0-5 in HH.	0.022***	0.021**	0.013*	0.013*	0.007	0.007
	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)
With Child 6-15 in HH.	0.010	0.009	0.014*	0.014*	0.013***	0.012***
	(0.009)	(0.009)	(0.007)	(0.007)	(0.005)	(0.004)
Household Size	-0	0	-0.004*	-0.004*	-0.005***	-0.004***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
HH Income \$40 – 75K	-0.001	-0	0.008	0.008	0.004	0.003
	(0.007)	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)
HH Income > 75K	0.007	0.007	0.037***	0.038***	0.030***	0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.005)	(0.005)
03 Management Related	0.027	0.038	0.009	0.018	0.018	0.027
Occupations	(0.023)	(0.037)	(0.020)	(0.032)	(0.018)	(0.024)
04 Engineers	-0.032	-0.019	-0.049***	0.009	-0.026**	-0.059*
	(0.038)	(0.061)	(0.014)	(0.043)	(0.013)	(0.032)
05 Math. and Computer Scientists	-0.025	-0.013	0.073**	0.112***	-0.027	-0.019
	(0.035)	(0.043)	(0.033)	(0.040)	(0.021)	(0.025)
08 Health Assessment and	0.025	0.083	0.010	0.045	-0.015	-0.016
Treating	(0.032)	(0.069)	(0.029)	(0.045)	(0.025)	(0.053)
09 College and University	-0.169**	-0.143	0.052	0.079	-0.026	0.043
Teachers	(0.076)	(0.117)	(0.136)	(0.122)	(0.089)	(0.097)
10 Other Teachers	-0.026	0.089	0.050***	-0.019	-0.019	0.021
	(0.019)	(0.073)	(0.016)	(0.078)	(0.018)	(0.051)
11 Lawyers and Judges	-0.150	-0.200	-0.078**	0.071	0.005	0.045
	(0.097)	(0.144)	(0.033)	(0.076)	(0.072)	(0.090)
12 Other Professional Specialty	0.041*	0.039	0.027	0.040	0.054***	0.074**
	(0.023)	(0.038)	(0.018)	(0.028)	(0.017)	(0.030)
13 Health Technologists and	0.067*	0.142*	0.014	0.019	0.007	0.045
Technicians	(0.039)	(0.076)	(0.027)	(0.045)	(0.026)	(0.050)
14 Engineering and Science	0.047	0.096*	0.001	0.001	0.015	0.043
Technicians	(0.034)	(0.050)	(0.027)	(0.041)	(0.022)	(0.035)
15 Other Technicians	0.051	0.069*	-0.010	0.031	0.025	0.017
	(0.037)	(0.042)	(0.026)	(0.036)	(0.026)	(0.029)

16 Sales Supervisors and	0.050*	0.156**	0.028	0.003	0.011	-0.017
Proprietors	(0.026)	(0.069)	(0.021)	(0.046)	(0.019)	(0.034)
17 Sales Representatives, Finance	0.024	-0.015	0.041	0.017	0.090***	0.148**
and Business Service	(0.033)	(0.059)	(0.028)	(0.056)	(0.032)	(0.065)
18 Sales Representatives,	-0.050	0.048	0.133*	0.118	0.051*	-0.010
Commodities except Retail	(0.054)	(0.069)	(0.070)	(0.075)	(0.028)	(0.040)
19 Sales Workers, Retail and	0.082**	0.205**	0.021	-0.040	0.034	0.003
Personal Services	(0.038)	(0.094)	(0.029)	(0.056)	(0.029)	(0.047)
21Supervisors, Administrative	-0.013	0.016	0.022	0.032	-0.037*	-0.019
Support	(0.025)	(0.045)	(0.040)	(0.049)	(0.019)	(0.028)
23 Secretaries, Stenographers, and	0.086**	0.134**	0.028	0.020	0.120	0.150
Typists	(0.038)	(0.066)	(0.031)	(0.044)	(0.082)	(0.093)
24 Financial Records Processing	0.096**	0.140**	0.015	0.016	0.041	0.055
	(0.038)	(0.062)	(0.028)	(0.042)	(0.043)	(0.049)
25 Mail and Message Distributing	0.042	-0.021	0.004	-0.011	0.015	0.062
	(0.042)	(0.130)	(0.033)	(0.077)	(0.030)	(0.055)
26 Other Administrative Support	0.067**	0.072	0.018	-0.018	0.014	0.043
Occupations, including Clerical	(0.033)	(0.059)	(0.027)	(0.041)	(0.027)	(0.040)
28 Protective Service Occupations	0.044	0.088	0.016	0.061	0.007	0.091**
	(0.035)	(0.096)	(0.036)	(0.060)	(0.023)	(0.041)
29 Food Service Occupations	0.063	0.189**	0.020	-0.031	0.029	0.018
	(0.038)	(0.087)	(0.032)	(0.056)	(0.030)	(0.048)
30 Health Service Occupations	0.076*	0.165**	0.018	0.013	0.050	0.091
	(0.039)	(0.081)	(0.030)	(0.052)	(0.042)	(0.070)
31 Cleaning and Building Service	0.057	0.160**	0.014	-0.002	0.021	0.077
	(0.038)	(0.070)	(0.032)	(0.053)	(0.029)	(0.051)
32 Personal Service	0.103**	0.151**	0.049	0.030	0.026	0.058
	(0.041)	(0.068)	(0.030)	(0.043)	(0.029)	(0.049)
33 Mechanics and Repairs	0.033	0.067	0.064	0.066	0.027	0.047
	(0.035)	(0.057)	(0.066)	(0.077)	(0.026)	(0.044)
34 Construction Trades	0.064	0.136*	0.002	-0.027	0.021	0.035
	(0.039)	(0.071)	(0.030)	(0.058)	(0.028)	(0.043)
35Other Precision Production	0.073*	0.163***	0.023	-0.006	0.014	0.018
	(0.040)	(0.060)	(0.028)	(0.046)	(0.027)	(0.037)
36 Machine Operators and	0.071*	0.181**	0.011	-0.029	0.027	0.041
Tenders	(0.039)	(0.072)	(0.032)	(0.055)	(0.030)	(0.044)
37 Fabricators, Assemblers,	0.067*	0.173**	0.042	0.009	0.019	0.031
Inspectors, and Samplers	(0.037)	(0.068)	(0.039)	(0.056)	(0.028)	(0.041)
38 Motor Vehicle Operators	0.057	0.037	0.008	0.009	0.020	0.020
	(0.039)	(0.083)	(0.032)	(0.057)	(0.029)	(0.047)
39 Other Transportation and	-0.001	0.098	-0.014	-0.019	0.017	0.021
Material Moving	(0.035)	(0.074)	(0.035)	(0.059)	(0.029)	(0.045)
40 Construction Laborer	0.051	0.154*	-0.035	-0.055	0.022	0.048
	(0.040)	(0.080)	(0.033)	(0.064)	(0.029)	(0.046)
41 Freight, Stock and Material	0.087	0.140*	0.019	-0.006	0.026	0.033
Handlers	(0.054)	(0.082)	(0.032)	(0.055)	(0.030)	(0.046)
42 Other Handlers, Equipment	0.047	0.168**	0.008	-0.032	0.019	0.034
Cleaners, and Laborers	(0.048)	(0.075)	(0.033)	(0.057)	(0.031)	(0.048)
44 Farm Related Workers	0.079**	0.174**	0.010	-0.026	0.029	0.066
	(0.038)	(0.071)	(0.032)	(0.057)	(0.030)	(0.046)
Internet Penetration	**0.539*** **	**0.481*** **	**0.143**	**0.183**	**0.288** **	**0.285** **
	(0.160)	**(0.163)**	**(0.127)**	**(0.134)**	**(0.119)**	**(0.115)**
Constant	-0.194***	-0.446**	-0.081**	0.089	-0.072**	-0.247**

	(0.053)	(0.181)	(0.039)	(0.159)	(0.032)	(0.102)
Job-by-city Covariates	N	Y	N	Y	N	Y
Observations	6936	6936	6553	6553	13809	13809
R-squared	0.07	0.08	0.07	0.07	0.09	0.09

Note: All models include MSA fixed effects. Occupation-by-city covariates include fractions of employees within each 2-digit occupation and MSA who are male, white, black, have high school degree, some college, college degree, advanced degree, work in industries of transportation and communication, trade, finance, services, or public administration, and work in private profit or private non-profit sectors. Also included are occupation's local labor market share, median log of wage, inter-quartile log of wage, and fraction of employees that have flexible work hours. Robust standard errors are estimated clustering on MSA. * indicates significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 5. Reduced-Form Estimates of Commute Time Model, 2000 PUMS

	Married Women		Men	
	(1)	(2)	(3)	(4)
Age	0.174***	0.174***	0.575***	0.574***
	(0.019)	(0.018)	(0.017)	(0.017)
Age Squared	-0.003***	-0.003***	-0.006***	-0.006***
	(0)	(0)	(0)	(0)
White	-1.532***	-1.498***	-0.018	-0.002
	(0.344)	(0.337)	(0.222)	(0.208)
Black	2.322***	2.329***	2.048***	2.034***
	(0.374)	(0.377)	(0.314)	(0.326)
High Scholl Degree	-0.731***	-0.640***	0.194***	0.229***
	(0.151)	(0.133)	(0.071)	(0.069)
Some College	0.126	0.181	0.276***	0.286***
	(0.153)	(0.134)	(0.098)	(0.098)
College Degree	0.935***	0.943***	0.762***	0.711***
	(0.181)	(0.187)	(0.231)	(0.226)
Graduate Degree	1.628***	1.603***	-0.182	-0.324
	(0.290)	(0.261)	(0.267)	(0.247)
Spouse			1.193***	1.191***
			(0.107)	(0.107)
With Child 0-5 in HH.	1.370***	1.354***	0.667***	0.649***
	(0.099)	(0.098)	(0.088)	(0.085)
With Child 6–15 in HH.	-0.535***	-0.533***	-0.091	-0.103
	(0.106)	(0.104)	(0.092)	(0.089)
Household Size	-0.455***	-0.452***	0.301***	0.313***
	(0.043)	(0.041)	(0.038)	(0.036)
HH Income $40 – 75K	0.320***	0.337***	0.330***	0.341***
	(0.097)	(0.095)	(0.079)	(0.075)
HH Income > 75K	1.278***	1.256***	1.118***	1.099***
	(0.151)	(0.148)	(0.146)	(0.142)
03 Management Related Occupations	1.908***	2.335***	1.741***	1.546***
	(0.247)	(0.506)	(0.239)	(0.525)
04 Engineers	1.074***	3.083***	1.155***	2.090***
	(0.411)	(1.185)	(0.273)	(0.795)
05 Math. and Computer Scientists	3.007***	4.387***	2.604***	3.340***
	(0.333)	(0.569)	(0.333)	(0.650)
08 Health Assessment and Treating	-0.434	-0.379	-1.485**	-0.359
	(0.662)	(1.024)	(0.603)	(1.228)
09 College and University Teachers	-1.924**	3.412*	-2.793***	0.201
	(0.862)	(1.956)	(0.922)	(2.106)
10 Other Teachers	-7.506***	-3.951***	-5.218***	-0.868
	(0.369)	(1.271)	(0.362)	(1.900)
11 Lawyers and Judges	-0.911	0.464	-0.947	-3.326
	(0.967)	(2.855)	(0.660)	(2.456)
12 Other Professional Specialty	-1.984***	1.559**	-2.100***	0.711
	(0.204)	(0.637)	(0.175)	(1.009)
13 Health Technologists and Technicians	-0.090	2.122**	-0.468	1.705
	(0.640)	(1.068)	(0.600)	(1.605)
14 Engineering and Science Technicians	2.347***	6.782***	0.791*	3.843***
	(0.595)	(1.043)	(0.438)	(1.216)
15 Other Technicians	3.615***	3.371***	2.792***	2.707***

	(0.373)	(0.668)	(0.446)	(0.741)
16 Sales Supervisors and	-1.611***	3.980***	-1.555***	2.511**
Proprietors	(0.368)	(1.082)	(0.364)	(1.080)
17 Sales Representatives, Finance	-1.752***	-3.124**	-0.679**	-4.056**
and Business Service	(0.273)	(1.558)	(0.336)	(1.799)
18 Sales Representatives,	2.259***	8.260***	2.597***	7.295***
Commodities except Retail	(0.408)	(1.080)	(0.287)	(1.002)
19 Sales Workers, Retail and	-3.976***	2.761*	-3.205***	2.712*
Personal Services	(0.630)	(1.419)	(0.615)	(1.438)
21Supervisors, Administrative	0.143	3.418***	-0.112	2.892***
Support	(0.411)	(0.755)	(0.447)	(0.864)
23 Secretaries, Stenographers, and	-0.096	3.904***	-0.016	3.984***
Typists	(0.542)	(0.996)	(0.585)	(1.324)
24 Financial Records Processing	0.176	4.643***	0.730	4.785***
	(0.586)	(1.047)	(0.580)	(1.025)
25 Mail and Message Distributing	-0.399	3.378*	-3.019***	5.746***
	(0.800)	(1.911)	(0.683)	(1.757)
26 Other Administrative Support	-0.095	1.157	-1.027*	0.525
Occupations, including Clerical	(0.568)	(1.025)	(0.533)	(0.847)
28 Protective Service Occupations	0.034	4.622**	-1.556**	2.642
	(0.861)	(1.885)	(0.668)	(1.744)
29 Food Service Occupations	-4.354***	2.308	-3.580***	1.958
	(0.713)	(1.562)	(0.653)	(1.517)
30 Health Service Occupations	-0.555	3.314***	-1.573**	1.725
	(0.666)	(1.216)	(0.694)	(1.730)
31 Cleaning and Building Service	0.610	5.096***	-2.378***	0.985
	(0.623)	(1.424)	(0.660)	(1.754)
32 Personal Service	-1.586***	3.159**	-1.509**	3.387**
	(0.582)	(1.218)	(0.598)	(1.598)
33 Mechanics and Repairs	2.594***	6.459***	0.015	2.849**
	(0.601)	(1.132)	(0.583)	(1.401)
34 Construction Trades	4.153***	10.447***	5.044***	9.022***
	(0.830)	(1.477)	(0.650)	(1.545)
35Other Precision Production	-0.472	5.480***	-0.701	3.599***
	(0.595)	(1.187)	(0.602)	(1.345)
36 Machine Operators and Tenders	0.151	6.061***	-1.077*	3.070**
	(0.649)	(1.417)	(0.637)	(1.553)
37 Fabricators, Assemblers,	0.558	6.950***	0.233	4.696***
Inspectors, and Samplers	(0.678)	(1.302)	(0.637)	(1.495)
38 Motor Vehicle Operators	-2.504***	1.576	-1.549**	3.569**
	(0.789)	(1.422)	(0.714)	(1.548)
39 Other Transportation and	1.275	7.537***	1.806***	6.669***
Material Moving	(1.075)	(1.653)	(0.665)	(1.596)
40 Construction Laborer	5.827**	13.929***	5.626***	10.816***
	(2.508)	(2.834)	(0.695)	(1.737)
41 Freight, Stock and Material	-0.629	5.467***	-1.286**	4.183***
Handlers	(0.632)	(1.462)	(0.650)	(1.557)
42 Other Handlers, Equipment	-0.339	6.301***	-0.761	3.934**
Cleaners, and Laborers	(0.827)	(1.652)	(0.643)	(1.765)
44 Farm Related Workers	0.732	6.945***	-1.091	3.227*

	(0.968)	(1.714)	(0.739)	(1.679)
Internet Penetration	**5.988****	**4.625****	**1.364**	**1.599**
	(2.704)	**(2.311)**	**(2.660)**	**(2.188)**
Constant	24.001***	5.690	12.845***	-3.926
	(1.012)	(3.475)	(0.735)	(3.755)
Job-by-city Covariates	N	Y	N	Y
Observations	832956	832956	1720931	1720931
R-squared	0.08	0.08	0.07	0.07

Note: All models include MSA fixed effects. Robust standard errors are estimated clustering on MSA. * indicates significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 6a. TSIV Estimates of the Effects of Telecommuting on Commute Time

	Married Women		Male	
	(1)	(2)	(3)	(4)
First-Stage				
Coefficient	0.539***	0.481***	0.288**	0.285**
Standard Error	0.16	0.163	0.119	0.115
# of Observations	6936	6936	13809	13809
Reduced-Form				
Coefficient	5.988**	4.625**	1.364	1.599
Standard Error	2.704	2.311	2.66	2.188
# of Observations	832956	832956	1720931	1720931
TSIV				
Coefficient	11.109*	9.615*	4.736	5.610
Standard Error	6.004	5.805	9.441	8.004
Job-by-city Covariates	N	Y	N	Y

Table 6b. TSIV Estimates of the Effects of Telecommuting on Commute Mode

	Married Women		Male	
	(1)	(2)	(3)	(4)
First-Stage				
Coefficient	0.539***	0.481***	0.288**	0.285**
Standard Error	0.16	0.163	0.119	0.115
# of Observations	6936	6936	13809	13809
Reduced-Form				
Coefficient	0.013	0.003	0.006	-0.043
Standard Error	0.047	0.036	0.05	0.037
# of Observations	849904	849904	174329	1743292
TSIV				
Coefficient	0.024	0.006	0.021	-0.151
Standard Error	0.087	0.075	0.174	0.143
Job-by-city Covariates	N	Y	N	Y

Note: All models include age, age squared, race, education, household composition, annual household income, and occupation and MSA fixed effects. Robust standard errors are estimated clustering on MSA.* indicates significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 7a. Robustness Check on Commute Time

	Married Women		Male	
	(1)	(2)	(3)	(4)
	A. OCCUPATION – MSA SIZE CELL >= 30			
First-Stage				
Coefficient	0.419**	0.346**	0.302***	0.325***
Standard Error	0.169	0.174	0.115	0.115
# of Observations	7157	7157	14724	14724
Reduced-Form				
Coefficient	5.427***	4.519***	1.285	0.909
Standard Error	2.086	1.713	2.212	1.839
# of Observations	864097	864097	1831544	1831544
TSIV				
Coefficient	12.952*	13.061	4.255	2.797
Standard Error	7.216	8.225	7.502	5.744
	B. OFFICE WORKERS			
First-Stage				
Coefficient	0.574***	0.532***	0.254	0.244
Standard Error	0.169	0.171	0.175	0.164
# of Observations	5477	5477	6974	6974
Reduced-Form				
Coefficient	5.369*	4.583*	1.858	0.966
Standard Error	3.051	2.355	2.054	2.137
# of Observations	654502	654502	845161	845161
TSIV				
Coefficient	9.354	8.615*	7.315	3.959
Standard Error	5.986	5.221	9.529	9.154
	C. TOPCODED COMMUTE TIME REPLACED BY 165 MIN			
First-Stage				
Coefficient	0.539***	0.481***	0.288**	0.285**
Standard Error	0.16	0.163	0.119	0.115
# of Observations	6936	6936	13809	13809
Reduced-Form				
Coefficient	6.088**	4.517*	1.63	1.806
Standard Error	2.792	2.473	2.856	2.5
# of Observations	832956	832956	1720931	1720931
TSIV				
Coefficient	11.295*	9.391	5.660	6.337
Standard Error	6.170	6.047	10.189	9.137
Job-by-city Covariates	N	Y	N	Y

Table 7b. Robustness Check on Commute Mode

	Married Women		Male	
	(1)	(2)	(3)	(4)
	A. OCCUPATION – MSA SIZE CELL >= 30			
First-Stage				
Coefficient	0.419**	0.346**	0.302***	0.325***
Standard Error	0.169	0.174	0.115	0.115
# of Observations	7157	7157	14724	14724
Reduced-Form				
Coefficient	0.032	0.022	0.035	0.023
Standard Error	0.043	0.033	0.047	0.036
# of Observations	881551	881551	1855151	1855151
TSIV				
Coefficient	0.076	0.064	0.116	0.071
Standard Error	0.107	0.101	0.162	0.114
	B. OFFICE WORKERS			
First-Stage				
Coefficient	0.574***	0.532***	0.254	0.244
Standard Error	0.169	0.171	0.175	0.164
# of Observations	5477	5477	6974	6974
Reduced-Form				
Coefficient	0.045	0.035	-0.059	-0.054
Standard Error	0.059	0.04	0.040	0.049
# of Observations	667751	667751	862045	862045
TSIV				
Coefficient	0.078	0.066	-0.232	-0.221
Standard Error	0.105	0.078	0.225	0.250
Job-by-city Covariates	N	Y	N	Y

Note: All models include age, age squared, race, education, household composition, annual household income, and occupation and MSA fixed effects. Robust standard errors are estimated clustering on MSA.* indicates significant at 10%, ** significant at 5%, and *** significant at 1%.

Table 8. Projection of Commute Time (Minute) onto Commute Distance (Mile)

	All	Women	Men
	(1)	(2)	(3)
Commute Distance	1.253	1.363	1.224
	(0.018)	(0.042)	(0.023)
Distance Squared	-0.002	-0.004	-0.0019
	(0.0003)	(0.001)	(0.0003)
Constant	7.279	6.742	7.375
	(0.143)	(0.229)	(0.203)
# Observations	44,218	21,404	22,814
Adj. R-squrae	0.739	0.684	0.765

Note: The sample includes only those who drive to work in the sample in Table 1

Appendix 1. A Monocentric City Model with Commuters and Telecommuters

In a closed city, each household has only one worker and all employment concentrates in the central business district (CBD). Workers commute to work at the CBD along a radial network. Commuting costs per mile traveled are e, so a worker who lives d miles from the CBD spends $2ed$ on daily commuting. All workers earn the same income y per day. Household utility is described by a strictly quasi-concave function $u(c,h)$, where c represents consumption of a composite non-housing good and h is consumption of housing that could be measured in square feet of floor space or number of rooms. The price of the composite good is assumed to be the same across different locations of the city and normalized to 1. The daily rental price of a unit of housing, denoted p, depends on location.

Initially, suppose all workers are identical. They maximize household utility to reach a constant level, $\bar{u}$. That is

$$\max_{\{c,h\}} u(c,h) = \bar{u} \quad \text{(A1)}$$

$$\text{s.t. } c + ph + 2ed = y .$$

Substitute $c = y - ph - 2ed$ into Eq. (A1) and notice that equilibrium housing price and consumption are both functions of distance to the CBD, i.e. d. We have

$$u\left(y - p(d)h(d) - 2ed, h(d)\right) = \bar{u} . \quad \text{(A2)}$$

Totally differentiating Eq. (A2) and applying the envelop theorem, we get the well-known conditions on the market equilibrium rent gradient that,

$$p'(d) = \frac{\partial p(d)}{\partial d} = -\frac{2e}{h(d)}, \qquad \text{(A3)}$$

and

$$p''(d) = \frac{\partial p^2(d)}{\partial d^2} = \frac{2eh'(d)}{h(d)^2}. \quad \text{(A4)}$$

Eqs. (A3) and (A4) imply that the housing price declines with commuting distance and the rent gradient gets flatter as distance increases since $h'(d) > 0$. Plotted on a plane with distance to the CBD as the x-axis and rent as the y-axis, the rent curve is a downward-sloping convex function. Intuitively, workers who live in the suburbs with longer commute are compensated by cheaper and larger homes.

Now, extend the model to including two types of otherwise identical workers: commuters (c) and telecommuters (tc). Because the latter commute less often than the former, the average daily commuting costs are lower for telecommuters than for commuters. Therefore, there are separate rent offer curves for the two types of workers, respectively. They are characterized as

$$p_i'(d) = -\frac{2e_i}{h_i(d)}$$

where $i = c, tc$. Assuming that housing is a normal good, then $h_c(d) < h_{tc}(d)$. Together with $e_c > e_{tc}$, we have

$$\left| p_c'(d) \right| > \left| p_{tc}'(d) \right|.$$

The rent offer of telecommuters declines slower than that of commuters. Figure A1 illustrates the two rent offer curves and the market rent gradient in equilibrium. The telecommuters' rent offer curve (CD) is flatter than commuters' rent offer curve (AB) while the two intersect at a certain distance $d = d_o$. Commuters outbid telecommuters for housing at locations closer to the CBD ($d < d_o$), as segment AO lies above CO, and vice versa for locations beyond d_o. The market equilibrium rent gradient is the upper segments of the two offer curves (AO and OD). This means in equilibrium commuters occupy the entire ring-shaped region around the CBD from distance 0 to d_o while telecommuters sort into the surrounding ring from d_o to d^*, the city edge determined by exogenous farmland rent. Thus, telecommuters have longer commutes than commuters.

Appendix 2. Imputation of Top-Coded Commuting Time in the PUMS

First, I estimate a Pareto distribution to approximate the right-hand tail of the commute time distribution, i.e.

$$f(x) = ab^a x^{-(a+1)}, \text{ for } b \le x \le \infty$$

where a is the parameter of the distribution, b is a constant from which commuting time is assumed to follow a Pareto distribution, x is observed individual commuting time equal to or greater than b. To obtain an estimate for a, I estimate $\Pr(x \ge t)$, where t is the top-coded value, i.e. 99 in PUMS, by the fraction of people commuting b or more minutes who are top-coded, and exploit the relationship $\Pr(x \ge t) = \left(b/t\right)^a$. Therefore,

$$\hat{a} = \frac{\ln\left(\hat{\Pr}(x \ge t)\right)}{\ln b - \ln t}.$$

Then, the top-coded values are replaced by the estimated conditional expectation of commuting time,

$$E(x \mid x \ge t) = t\hat{a}(\hat{a} - 1)^{-1}$$

where t is the top-coded value, i.e. 99 in PUMS. Thus, different values for b yield different estimates of a and the imputing value for top-coded observations.

For instance, let $b = 50$, then 378,211 observations have commuting time equal to or above 50 minutes, 16.4 percent of which are top-coded observations. Thus, $\hat{a} = \ln(0.164)/\left(\ln(50) - \ln(99)\right) = 2.65$. The conditional expectation for top-coded individuals equals 159.1. When b is varied from 40 to 90 in increments of 10, the conditional expectation estimates vary from 123 to 165 with an average of 150.

Figure A1. Bid Rent Curves in a Monocentric City with Telecommuters and Commuters

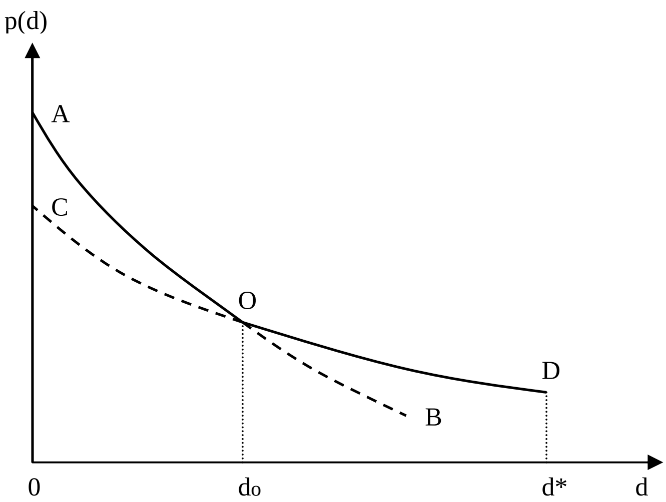


Table A1. CPS and NHTS Sample Construction

	May 2001 CPS	2001 NHTS
Original sample	131,997	160,758
15 or older, employed with information on working at home	50,743	65,697
Not self-employed	45,217	
Reasonable commute distance and speed		62,283
MSA residents	32,272	50,810
Final sample without missing values on any covariates	29,147	47,730

Note: Reasonable commute distance refers to one-way commute time below 180 minutes and commute distance below 180 miles; reasonable speed refers to speed between 0.01 mile per minute and 1.5 miles per minute.