ABSTRACT

Title of Dissertation: TWO EMPIRICAL ESSAYS IN ENVIRONMENTAL AND URBAN ECONOMICS

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Externalities associated with automobile use have long been an important topic in environmental and urban economics. Air pollution and traffic congestion constitute two main external costs of driving (Parry, Walls and Harrington 2007). Because pricing approaches such as higher fuel taxes and road pricing are unpopular, various travel demand management (TDM) programs aiming to control vehicle travel demand through non-pricing approaches have been adopted by government agencies across the country. These programs provide public information, use persuasion, subsidize transit riding, and promote carpooling and telecommuting. However, whether these programs generate incentives for people to reduce driving remains an open question.

I address this question with respect to two types of TDM strategies: telecommuting and public information provision. The first essay examines whether telecommuting opportunities lead employees to have longer commute lengths.

Because telecommuting is often jointly chosen with commuting patterns and no single dataset contains sufficient information to solve the endogeneity problem, I use a two-sample instrumental variables technique to estimate the causal impact of telecommuting on commute length. The data for the project are assembled from the May 2001 Current Population Survey (CPS) and the 2000 Census 5% Public Use Micro-data Series (PUMS). The results suggest that telecommuting increases married female workers' one-way commute time by 9 – 12 minutes, but the effect on male workers' commute length is not precisely estimated. Although telecommuting may still cut down total commute miles, it is less effective than expected, in particular for married women.

The second essay assesses the effectiveness of the Air Quality Action Days program in the Baltimore metropolitan area in getting cars off the road on high ozone days. The program asks people to reduce vehicle trips on code red days when the ozone level is forecast to exceed the EPA's standard. I look at traffic volumes on highways in the Baltimore area, and using a regression discontinuity design, measure the extent that traffic is lower due to the announcement. I find that the program generally has little effect except that it reduces morning inbound traffic by 4-5 percent. Evening outbound traffic declines correspondingly.

TWO EMPIRICAL ESSAYS IN ENVIRONMENTAL AND URBAN ECONOMICS

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Dedication

This work is dedicated to my parents, who have always been the source of my aspiration, energy and strength, and to my wife Ruoyun (Rebecca), for her constant support, encouragement and love.

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I am pleased that I chose environmental economics as my major field and am extremely fortunate to have Maureen Cropper as my advisor. She has spent uncounted hours instructing and mentoring me. Beyond this dissertation, Maureen’s help and support has been complete and unconditional: from obtaining external funding to recommending me for a Resources for the Future internship; from eliciting information from knowledgeable researchers for my projects to supporting my participation in academic workshops and conferences. I think the best way to return her great support is to be a sound environmental economist, which I will strive to be.

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1 Introduction

Automobile use generates significant negative externalities that can be quite costly to the society. Some economists estimate that external costs amount to 5 cents per mile in the form of congestion, 2 cents per mile in air pollution and 3 cents per mile in accidents (Parry, Walls and Harrington 2007). The externalities associated with driving are not an easy problem to solve. For instance, road capacity expansion has not proved effective in mitigating congestion due to latent demand (e.g. Small 1992a), and it exacerbates the air pollution problem by encouraging more driving. Economic theory suggests that excess driving can be reduced by adding the extra social cost caused by vehicle driving to a driver's personal cost calculation. This can be accomplished with instruments like higher fuel taxes and/or a congestion toll. However, in the US where car ownership is prevalent and demand for vehicle travel is price inelastic, it is not surprising that these pricing approaches have little political support. Meanwhile, government agencies such as urban planning boards have been interested in controlling the demand for vehicle travel directly. They have developed various travel demand management (TDM) programs that provide public information, use persuasion, subsidize transit riding, and promote carpooling and telecommuting. However, whether these programs generate incentives for people to reduce driving remains an open question.

1.1 Objective of the dissertation

This dissertation evaluates two distinct TDM strategies: telecommuting and a public information program. The focus of Chapter 2 is the impact of telecommuting on total commute miles. Telecommuting refers to working from home instead of traveling to work at least two days every month. In addition to being a favorable arrangement between employers and employees, telecommuting is increasingly used as a TDM strategy in order to mitigate urban congestion and air pollution attributable to commute trips. However, to what extent telecommuting reduces vehicle miles traveled (VMTs) depends on how it affects commute VMTs and non-commute VMTs. The impact of telecommuting on commute VMTs depends on the effect of telecommuting on one-way commuting length as well as telecommuting frequency. The naïve conclusion that telecommuting reduces total commute miles in the same proportion as it reduces commuting frequency could be wrong because telecommuting may actually increase one-way commuting length.

The goal of Chapter 2 is to empirically measure the impacts of telecommuting on one-way commute length and the probability of driving to work. One of the difficulties is that telecommuting is not a random choice. Individuals who telecommute could be systematically different from non-telecommuters in unobserved ways that are also correlated with commuting behavior. I employ instrumental variable methods to obtain consistent estimates, and develop an instrumental variable that captures variation in telecommuting opportunity across occupation and city size. Another difficulty is that there exists no single data set that contains telecommuting, commuting and the instrumental variable. The problem is tackled by using the two-sample instrumental variable technique, initially developed in Angrist and Krueger (1992). The two samples come from the May 2001 CPS and 2000 PUMS, both of which are nationally representative.

Chapter 3 looks at a specific public information program---the Air Quality Action Days program in the Baltimore metropolitan area---which features a code red day alert when ground-level ozone is forecast to exceed the EPA's standard. The program not only warns the public of high ozone levels but also tries to lower ozone concentrations on those days by persuading people not to drive. The program can be viewed as a TDM initiative that aims to influence vehicle travel episodically for environmental purposes. It is unclear, however, whether an individual would forego driving on code red days even if he/she internalizes the environmental cost resulting from his/her driving. Driving might still be the optimal mode choice because a person has a smaller risk of being exposed to bad air when driving than when walking to transit. This chapter conducts an evaluation of effectiveness of the program in reducing on-road vehicles. A regression discontinuity design is employed to overcome potential omitted variable bias, since the code red day is a discontinuous function of an observed continuous variable, forecast ozone level.

In sum, the dissertation studies two popular TDM strategies from an economic perspective. Potential behavioral responses are taken into account and state-of-the-art econometric techniques are used in the analysis to carefully examine the effectiveness of the strategies in lowering vehicle travel. Both positive and negative findings should be useful to economists. The former may lead us to re-think TDM programs and consider combining pricing approaches with TDM. A negative finding could strengthen the argument for a complete pricing strategy.

1.2 Contribution to the Literature

Most empirical studies about telecommuting are designed to identify what factors explain the choice of telecommuting. Relatively few studies examine the impacts of telecommuting on commute length or total VMTs. The results from previous studies are mixed, with earlier ones suggesting a reduction in total VMTs and later ones showing positive effects on one-way commute distance and total commute miles. But most studies are subject to two critical shortcomings. First, telecommuting is assumed to be exogenous in explaining commute distance or miles. Second, the datasets used in the analyses are usually small and not representative.

The main contribution of Chapter 2 is that I tackle the endogeneity issue with an instrumental variable procedure and use large, nationally representative samples assembled from the 2001 CPS and 2000 PUMS. The instrumental variable measures the internet penetration for working from home across different occupation by city size cells, which should capture in exogenous telecommuting opportunity for individuals. Because of the data constraints mentioned in the previous section, I apply the two-sample instrumental variable technique of Angrist and Krueger (1992) to information on telecommuting from the May 2001 CPS and information on commuting from the 2000 PUMS. As both datasets are national samples, the results have implications for different regions and working groups.

The main findings are that telecommuting leads married female workers' one-way commute time to increase by 9 – 12 minutes and has a smaller, positive, but statistically insignificant effect on men's commute time. Exploring heterogeneous impacts between married women, single women and men is an innovation to the literature. It is plausible to expect that married women are more responsive to lower commuting costs as they are more often the secondary earner in a two-earner household and are likely to be more constrained in workplace locations. The results confirm these expectations.

Another contribution is to apply the same method to the probability of driving to work. The OLS estimates using the 2001 National Household Travel Survey (NHTS) data show that the propensity of driving to work declines among telecommuters. This result implies that telecommuting provides an extra bonus by changing commute modes in favor of transit. However, the two-sample instrumental variables estimates indicate that telecommuting has a positive but statistically insignificant effect on commute mode choice. They suggest that the OLS estimates could be misleading without correcting the endogeneity problem. Overall, the chapter suggests that telecommuting is less effective in lowering total commute miles than people think it is, in particular for married women.

Chapter 3 contributes to the literature by examining a public information program in Baltimore, and exploiting the program's institutional features to identify the traffic reduction attributable to the program. Similar advisory programs have been implemented in other urban areas that have ozone problem. Earlier studies either rely on survey respondents' stated information or are unable to detect a change in traffic caused by the program. Only the recent study by Cutter and Neidell (2007) uses the same econometric technique and reaches similar conclusions as my study does, but instead looks at the San Francisco Bay area. I find that the code red day announcements result in morning traffic reductions by 3 – 5%. This reduction occurs only for inbound traffic in the morning and outbound traffic in the evening.

1.3 Plan of the Dissertation

Chapters 2 and 3 are both self-contained essays. Chapter 2 examines the impact of telecommuting on one-way commuting length and on the probability of driving to work. Chapter 3 estimates the effect of code red day announcements on traffic volumes in the Baltimore Metropolitan area. Each chapter starts with an introduction of the research question, methodology and main findings. More detailed research or institutional background is provided next, and followed by a simple theoretical model to convey the key intuitions. Empirical methods as well as the data used are described. The main results and sensitivity checks are presented in subsequent sections. Each essay ends with a further discussion of the findings and conclusions. Chapter 4 summarizes the main findings in both essays and draws some common conclusions. It also discusses the questions stemming from the study that deserve future research.

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

2.1 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.[1] 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.[2] At first blush it would appear that greater telecommuting should decrease

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

[2] 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

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 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

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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.

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.[3]

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.

[3] 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.

The rest of the paper is organized as follows: Section 2.2 defines telecommuting and provides background information about telecommuting and relevant studies. Section 2.3 presents baseline estimates of the "effect" of telecommuting on journey-to-work from OLS analysis of the 2001 Nationwide Household Transportation Survey (NHTS). Section 2.4 describes the identification strategy and the data. TSIV estimation results appear in Sections 2.5 and 2.6, with discussion and conclusions following in Sections 2.7 and 2.8.

2.2 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.[4] Among them 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.[5] 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

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

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

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.

2.3 Theory and Empirical Liteature

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 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.

2.4 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.[6] 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. 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.[7]

Table 2-1 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

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[6] 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.

[7] 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.

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 2-1 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 2-1 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. length or travel mode) as the dependent variable and telecommuting status, together with other relevant variables, as the explanatory variables. Table 2-2 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.

2.5 **Empirical Strategy**

2.5.1 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 2-2 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.

2.5.2 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.[8] 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

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

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

[8] 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.

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

$$\widehat{\beta}^{TSIV} = \left(\widehat{X}_2'\widehat{X}_2\right)^{-1}\widehat{X}_2'y_2,$$ [9]

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 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),

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

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[9] 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.

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,

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

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

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

where $\hat{\sigma}_1$ and $\hat{\sigma}_2$ are estimated standard errors of $\hat{\lambda}_1$ and $\hat{\lambda}_2$, respectively.[10]

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[10] 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: $t^2_{TSIV} = \frac{t_1^2 t_2^2}{t_1^2 + t_2^2}$. When t_1, the first-stage *t*-statistic outweighs t_2, t_{TSIV} approaches t_2.

2.5.3 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 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.[11] 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[12] 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.[13]

Table 2-3 presents descriptive statistics for telecommuters and non-telecommuters in the CPS sample. Telecommuters are 3 – 4 years older than commuters on average, 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

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

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

[13] In the notation of section 2.5.2, the condition on the joint sample can be formally written as

$$\underset{n_1\to\infty}{p\lim}\left(Z_1'X_1/n_1\right)=\underset{n_2\to\infty}{p\lim}\left(Z_2'X_2/n_2\right)=\Sigma_{ZX}\,.$$

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.

opportunities to telecommute. Finally, a higher proportion of telecommuters than non-telecommuters live in large MSAs with populations over one million. As in Table 2-1, Table 2-3 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 2-2 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.

2.6 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 2-4. In general, the estimates reflect the differences between telecommuters and commuters in Table 2-3. 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 2-4 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.

2.7 Reduced-Form and TSIV Estimates

2.7.1 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 2-5. 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.

2.7.2 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 2-6a 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.

2.7.3 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.[14] 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

[14] 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.

mode choice directly, TSIV produces consistent estimates of the effects of telecommuting on travel mode choice. Table 2-6b 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. 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.

2.7.4 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 2-7a and 2-7b 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 2-7a and 2-7b 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 2-7a 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.

2.8 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 2-8 shows the coefficients of models that project commute time onto commute distance and distance squared.[15] 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 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

[15] 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.

and 5.5 percent declines relative to the before-telecommuting commute times and commute miles, respectively.

2.9 Conclusion

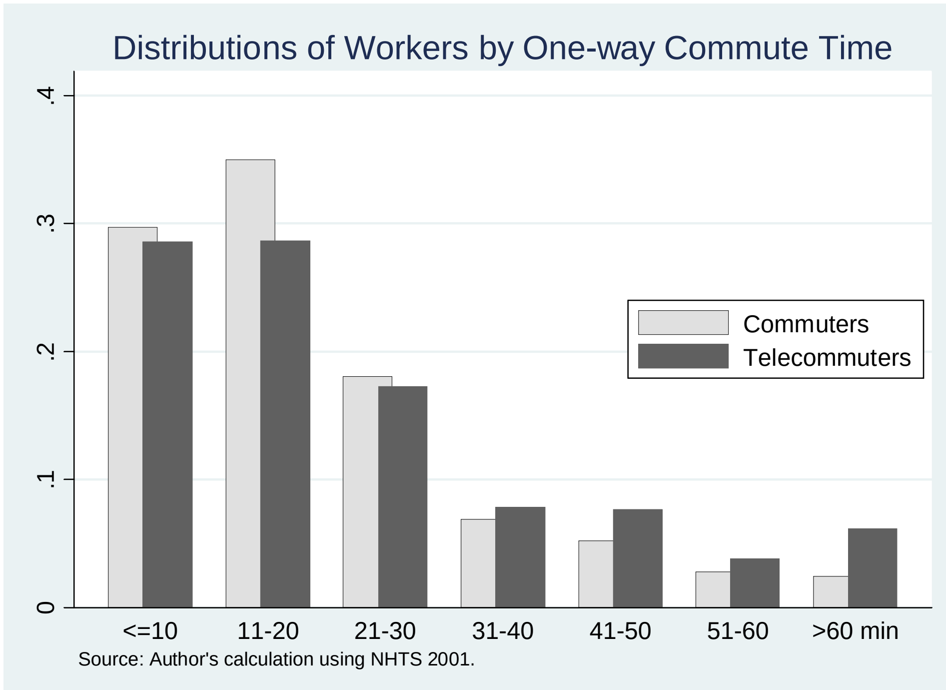
Telecommuting has been promoted as a means to deal with congestion and automobile emissions by researchers and public policy makers. However, there are concerns that telecommuting workers will make a longer commute in response to the lower commute frequency. Naïve (OLS) estimates based on the NHTS show 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.

Figures and Tables for Chapter 2

Figure 2-1. Distributions of Telecommuters and Commuters by Commute Time and Distance



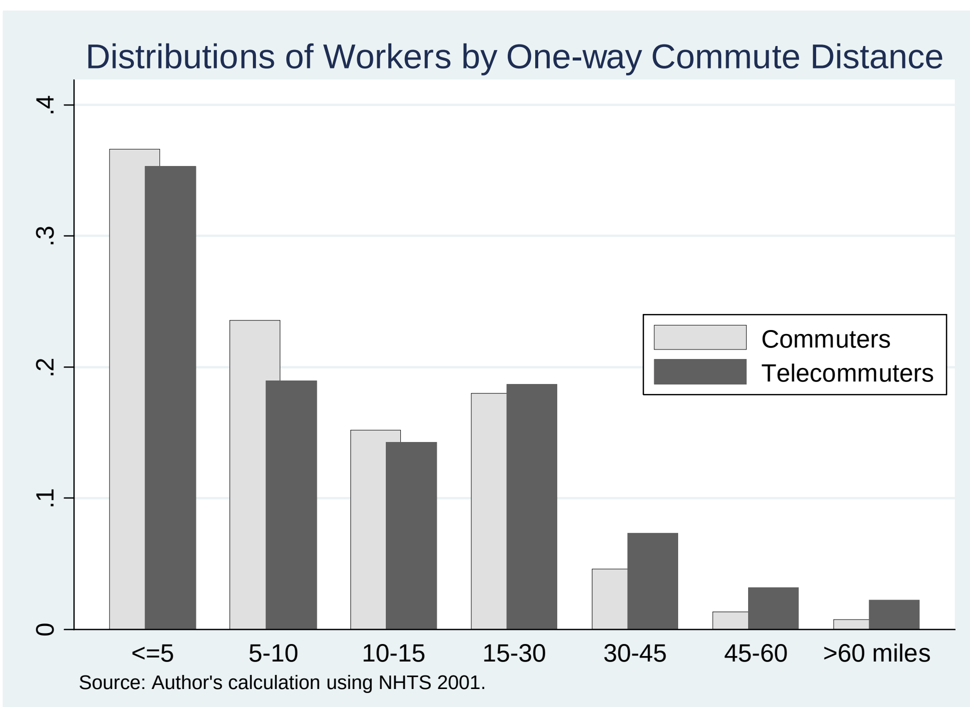
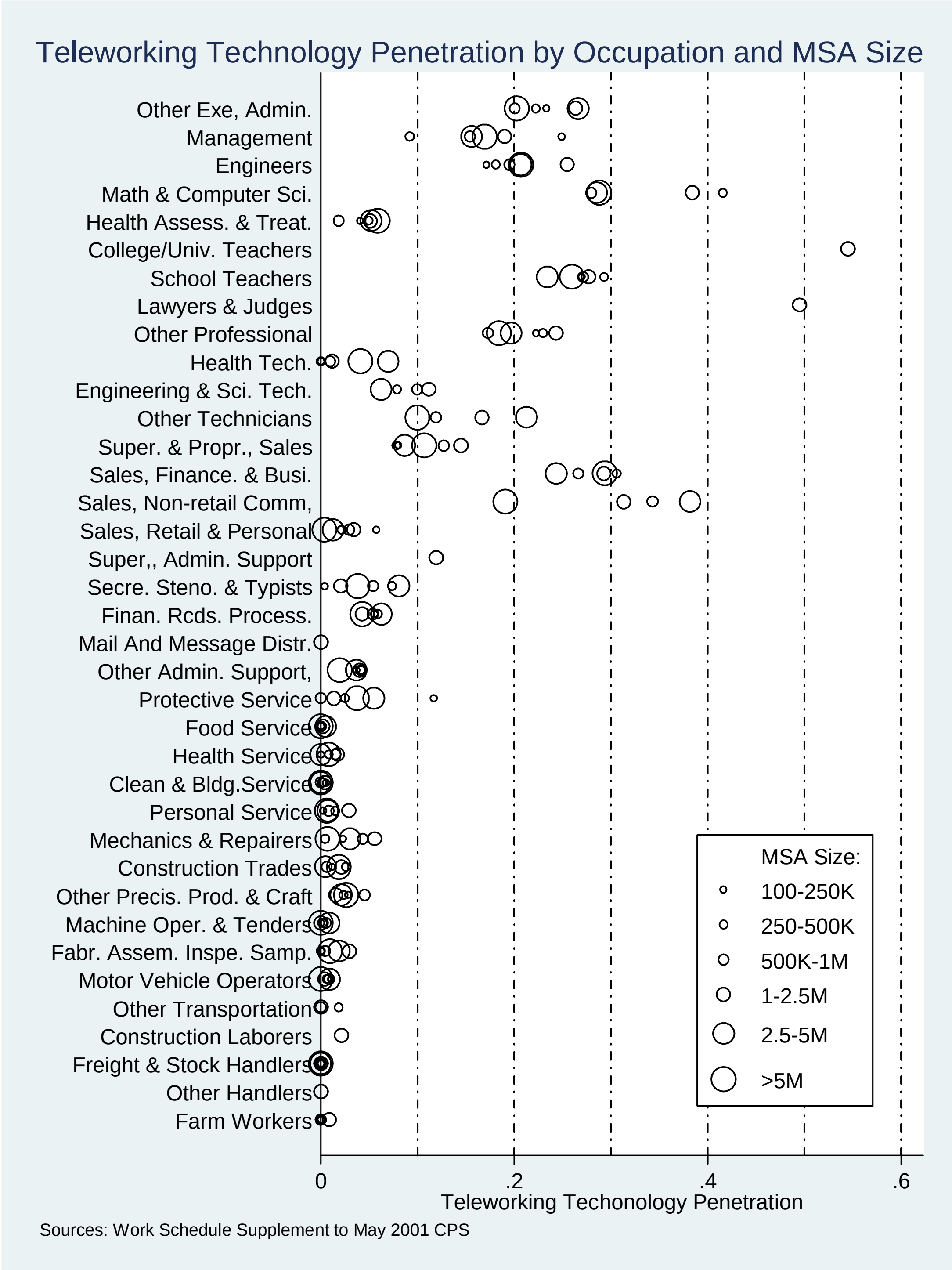


Figure 2-2. Internet Penetration by 2-Digit Occupation and MSA size (2001 CPS)



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 2-1. 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 2-2. 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-squared	0.11	0.17	0.13
# Observations	14176	8939	24615

Note: The sample is the same as in Table 2-1. 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 2-3. Summary 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 2-4. 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 Proprietors	0.050*	0.156**	0.028	0.003	0.011	-0.017
	(0.026)	(0.069)	(0.021)	(0.046)	(0.019)	(0.034)
17 Sales Representatives, Finance and Business Service	0.024	-0.015	0.041	0.017	0.090***	0.148**
	(0.033)	(0.059)	(0.028)	(0.056)	(0.032)	(0.065)
18 Sales Representatives, Commodities except Retail	-0.050	0.048	0.133*	0.118	0.051*	-0.010
	(0.054)	(0.069)	(0.070)	(0.075)	(0.028)	(0.040)
19 Sales Workers, Retail and Personal Services	0.082**	0.205**	0.021	-0.040	0.034	0.003
	(0.038)	(0.094)	(0.029)	(0.056)	(0.029)	(0.047)
21Supervisors, Administrative Support	-0.013	0.016	0.022	0.032	-0.037*	-0.019
	(0.025)	(0.045)	(0.040)	(0.049)	(0.019)	(0.028)
23 Secretaries, Stenographers, and Typists	0.086**	0.134**	0.028	0.020	0.120	0.150
	(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 Occupations, including Clerical	0.067**	0.072	0.018	-0.018	0.014	0.043
	(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 Tenders	0.071*	0.181**	0.011	-0.029	0.027	0.041
	(0.039)	(0.072)	(0.032)	(0.055)	(0.030)	(0.044)
37 Fabricators, Assemblers, Inspectors, and Samplers	0.067*	0.173**	0.042	0.009	0.019	0.031
	(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 Material Moving	-0.001	0.098	-0.014	-0.019	0.017	0.021
	(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 Handlers	0.087	0.140*	0.019	-0.006	0.026	0.033
	(0.054)	(0.082)	(0.032)	(0.055)	(0.030)	(0.046)
42 Other Handlers, Equipment Cleaners, and Laborers	0.047	0.168**	0.008	-0.032	0.019	0.034
	(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 2-5. 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 Proprietors	-1.611***	3.980***	-1.555***	2.511**
	(0.368)	(1.082)	(0.364)	(1.080)
17 Sales Representatives, Finance and Business Service	-1.752***	-3.124**	-0.679**	-4.056**
	(0.273)	(1.558)	(0.336)	(1.799)
18 Sales Representatives, Commodities except Retail	2.259***	8.260***	2.597***	7.295***
	(0.408)	(1.080)	(0.287)	(1.002)
19 Sales Workers, Retail and Personal Services	-3.976***	2.761*	-3.205***	2.712*
	(0.630)	(1.419)	(0.615)	(1.438)
21Supervisors, Administrative Support	0.143	3.418***	-0.112	2.892***
	(0.411)	(0.755)	(0.447)	(0.864)
23 Secretaries, Stenographers, and Typists	-0.096	3.904***	-0.016	3.984***
	(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 Occupations, including Clerical	-0.095	1.157	-1.027*	0.525
	(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, Inspectors, and Samplers	0.558	6.950***	0.233	4.696***
	(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 Material Moving	1.275	7.537***	1.806***	6.669***
	(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 Handlers	-0.629	5.467***	-1.286**	4.183***
	(0.632)	(1.462)	(0.650)	(1.557)
42 Other Handlers, Equipment Cleaners, and Laborers	-0.339	6.301***	-0.761	3.934**
	(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 2-6. TSIV Estimates of the Effects of Telecommuting on Commute Time and Mode

Table 2-6a. 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 2-6b. 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 2-7. Robustness Check of the TSIV Estimates

Table 2-7a. 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 2-7b. 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 2-8. 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-squared	0.739	0.684	0.765

Note: The sample includes only those who drive to work in the sample in Table 2-1.

3 Do People Drive Less on Code Red Days?

3.1 Introduction

By 2007, 347 counties with 141 million residents were designated by EPA as ground-level ozone nonattainment areas.[16] This means that nearly half of the US population breathes air with ozone concentration above a harmful level. Besides the established fact that ozone has adverse effects on the respiratory system, recent studies (e.g., Bell et al. 2004) also link ozone levels with increases in mortality. Therefore, bringing the ozone levels into compliance with the EPA standard is a goal of high priority for public policy.

Ozone is formed when its precursors, oxides of nitrogen (NOx) and volatile organic compounds (VOCs), react in the atmosphere. Peak ozone levels typically occur on hot, dry and sunny summer days. Emissions from motor vehicle exhaust, industrial facilities and electric utilities are the main sources of NOx and VOCs. Dramatic increases in the number of cars and miles they are driven contribute significantly to the ozone problem in urban areas, in spite of the fact that individual vehicles are getting cleaner. According to the EPA (2003), motor vehicles account for 56% and 45% of emissions of NOx and VOC nationwide, respectively.

A number of metropolitan areas have implemented public information programs that aim at mitigating the ozone problem by encouraging voluntary driving reductions on high ozone days. Examples include the Air Quality Action Days (AQAD) program in the

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[16] See http://www.epa.gov/air/oaqps/greenbk/o8index.html

Washington-Baltimore metropolitan area, the Spare the Air (STA) program in the San Francisco Bay area, and the Ozone Action Days program in Atlanta, to name a few. Undoubtedly, these programs have low implementation and enforcement costs, in contrast to mandatory control programs. They also take advantage of the episodic feature of the ozone problem, a strategy that theoretically promotes economic efficiency (Teller 1967, Krupnick 1988). However, the first question that needs to be addressed is how effective these programs are in getting cars off the road. People receiving forecast information may cancel trips due to the concerns about getting unhealthy exposure and/or the environmental impacts of driving on those days. Nevertheless, for many people, including most commuters, it is very costly to change travel schedules, if not impossible. The question is whether the information provided creates enough incentives for the recipients to take action.

Identifying the impact of the programs on vehicle driving also serves a practical purpose in air quality regulation. These public information programs all fall into the category of Voluntary Mobile Source Emission Reduction Programs (VMEPs). Since 1997, the U.S. EPA allows states with non-attainment areas to claim credits up to 3% of projected emissions reductions for VMEPs when filing State Implementation Plans (SIPs). To do so requires that mobile emission reductions through voluntary programs be quantified.

Several studies have looked at how these voluntary information programs impact travel behavior. Henry and Gordon (2003), MWCOG (2003), and Fox and Sarkar (2002) use individual survey data to examine to what extent the ozone alerts have altered behavior. They all find that a significant share of respondents reported taking actions during ozone episodes to help abate pollution. For example, Fox and Sarkar report that in the Washington-Baltimore area, 7-9 percent of respondents said they drove less on code red days, days when the ozone levels are predicted to exceed the EPA standard. A common issue, however, with the self-reported information is that it may be biased due to recollection difficulty or other subjective factors. Instead, Cummings and Walker (2000), Cutter and Neidell (2007) and Welch et al. (2005) directly examine traffic volumes in Atlanta and the San Francisco Bay area and train ridership in Chicago, respectively. Cummings and Walker and Welch et al. found either the traffic reductions were too small to be surely attributed to the program or the ozone advisories increased transit ridership only in a small part of the Chicago area. To the contrary, Cutter and Neidell found that STAs reduce total daily traffic by 2.5 to 3.5 percent, with most effects occurring during and just after the morning peak hours.

The focus of this study is to examine the effectiveness of the AQAD program in the Baltimore area, an area relying more on automobile driving than the Chicago, San Francisco and Washington DC metropolitan areas.[17] The program forecasts daily ozone level one day ahead and uses color codes to indicate expected ozone severity. When the

[17] Besides a bus system, Baltimore's transit system consists of a single-line metro subway and a three-line light rail, most parts of which overlap. In terms of commuting, the percentage of drivers is higher and the percentage of rail riders is lower than the national average, based on data from NHTS 2001. See Table A2 for a comparison of the distributions of commuters by commute mode across several cities.

ozone level is predicted to reach or exceed the one-hour ozone standard, 125 ppb, a code red is announced. I use a regression discontinuity (RD) design to see whether traffic volumes are lower on code red days due to the announcement. The study is closest to Cutter and Neidell in methodology, and obtains somewhat similar results. The main finding is that the code red day announcement reduces inbound traffic volumes during morning peak hours by 3-5%. Outbound traffic volumes in the evening peak hours fall correspondingly. In contrast, on code orange days, when ozone levels are predicted to exceed 105 ppb but lie below 125 ppb, I do not observe a reduction in vehicle driving.

The rest of the chapter is organized as follows. Section 3.2 documents the details of the AQAD program. Section 3.3 presents a theoretical account of potential behavioral changes in response to code red days. Sections 3.4 and 3.5 describe the empirical methods and data used, respectively. Section 3.6 presents the results, and section 3.7 discusses the policy implications of my findings.

3.2 AQAD Program in Baltimore Area

The Baltimore area, with over 2.5 million residents in 2000, consists of five counties[18] and Baltimore city. It is designated as a nonattainment area by EPA under both the 1-hour and 8-hour ozone standards. Since the mid-1990s the area has been implementing the AQAD program jointly with the Washington metropolitan area. Under the coordination of the Metropolitan Washington Council of Governments (MWCOG), a

[18] They are Anne Arundel, Baltimore, Carroll, Harford and Howard. See http://www.epa.gov/oar/oaqps/greenbk/baltimo.html for a regional map. The designated area is different from the census MSA definition.

daily forecast of the ozone level[19] is conducted for each area by a panel of meteorologists every day from May 1st to mid-September.

The ozone level is predicted as a quadratic function of a vector of variables including maximum and average surface temperatures, wind speed, relative humidity, solar zenith angel, and lagged ozone observations. Note that the predicting variables measure only the most relevant air and climatological conditions. Because they do not include variables that forecast vehicle travel demand and electric utility production, the model does not account for human behavior. The parameters of the function are estimated using historical observations and remain unchanged for the current year. The model produces forecasts for each of seven locations in Baltimore area where ozone monitoring stations are located. The highest one is chosen as the initial forecast for the area.

The expert panel meets on a conference call at 3:00 pm every afternoon to discuss and make adjustments to the initial forecast. This stage is subjective to the extent that it relies on the experience of the participants. A personal communication with one of the panel members indicates that the rational for this subjective procedure is multi-fold. First, some factors are hard to quantify or are insignificant in model estimation, e.g., the direction of wind from outside the area, but need to be taken into account. The day of the week is sometimes taken into account to address concerns about traffic. The panel also needs to consider different versions of weather forecasts as well as to adjust ozone forecasts at the lower and upper ends because the model seems to perform better in the

[19] The one-hour ozone level was forecast until 2003. Since 2004, eight-hour levels have been forecast..

middle range of ozone levels than at the extremes. Although the changes often involve only a couple of units, they may result in a shift of the air quality category in which the day falls.

A color code is assigned to the day based on the consensus forecast value. Table 3-1 shows the ranges of forecast one-hour ozone concentrations and the corresponding code colors. When the ozone level is predicted to exceed the EPA standard, i.e. 125 ppb, a red code is designated and the day is called a code red day. The last column in Table 3-1 shows the distribution of summer days across air quality categories. 28 days were announced as code red days in 2001 through 2003, accounting for 6.8 percent of the season. Code orange days indicate that the ozone concentration will reach a level unhealthy for sensitive populations. These days account for 10.6 percent of the period.

The forecast as well as the code color are publicized through various communication channels once they are available. People who subscribe to a mailing list receive email notification. Local employers who enroll in the clean air partner program receive an email or fax. Major newspapers and TV and radio stations will report air quality forecasts together with weather forecasts. News sources will highlight code red days to enhance visibility for the program. People are urged to take actions to reduce ozone precursors emissions on high ozone days. On the top of the action list is reducing driving by all means, including carpooling, teleworking, riding transit, and consolidating trips.

3.3 Theory

A simple discrete choice model can be used to analyze individual's choice between driving and its substitutes on code red days. Specifically, we consider staying/working at home and using public transit as the alternatives an individual may choose. Other travel options such as carpool and bicycle may be incorporated into the framework easily and would not affect the main results obtained below.

Suppose an individual chooses to drive (d), to ride public transit (p) or stay/work at home (h) in order to maximize her utility

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where i indexes individual, $j \in \{d, p, h\}$. The utility is the sum of a deterministic part V and an idiosyncratic part ε. Further assume that the deterministic utility is a weighted linear combination of travel benefits and a variety of travel costs. That is

$$V_{ij} = \beta_0 B_{ij} + \beta_1 TC_{ij} + \beta_2 HC_{ij} + \beta_3 EC_{ij}$$

where B stands for trip benefit ($B_h = 0$), TC is travel cost, including gas, bus fare, and time, HC is health cost resulting from exposure to bad air quality, and EC is the environment cost associated with one's choice. The model assumes that everybody has common weights, β's, and $\beta_0 > 0$, $\beta_1, \beta_2, \beta_3 < 0$ although the benefits/costs of each choice vary by individuals. In one case, people may differ in the extent that they internalize the negative impact on air quality for the same amount of driving, but they value air quality equally. Also, people with existing respiratory problem may have greater health costs than those without when exposed to the same air pollution.

We assume that ε_{ij} are independently distributed as type-I extreme value. Let y_i denote the choice of individual i that maximize the utility, i.e. $y_i = \arg\max(U_{id}, U_{ip}, U_{ih})$. The probability of choosing j is

$$\Pr(y_i = j \mid x_i) = \exp\left(\sum_{k=0}^{3} \beta_k x_{ijk}\right) / \left[\sum_j \exp\left(\sum_{k=0}^{3} \beta_k x_{ijk}\right)\right]$$

where $x_{\cdot 0} = B$, $x_{\cdot 1} = TC$, $x_{\cdot 2} = HC$, and $x_{\cdot 3} = EC$. For all individuals,

$$\partial p_j(x) / \partial x_{jk} = p_j(x)[1 - p_j(x)]\beta_k \tag{3-1}$$

and

$$\partial p_j(x) / \partial x_{lk} = -p_j(x) p_l(x) \beta_k, \ l \neq k. \tag{3-2}$$

We are interested in how probabilities of choosing different alternatives change when it is a code red day. Equations (3-1) and (3-2) tell us that the probability change for any alternative depends on the changes in each benefit/cost factors for the option itself and all others on code red days. To derive further results from the model, we assert the following changes and relationships

(i) $\Delta B_d = \Delta B_p = \Delta B_h = 0$,

(ii) $\Delta TC_d \leq 0 = \Delta TC_h \leq \Delta TC_p$,

(iii) $0 = \Delta HC_h \leq \Delta HC_d < \Delta HC_p$,

(iv) $\Delta EC_p, \Delta EC_h \leq 0 \leq \Delta EC_d$.

Relationship (i) states that the benefit from making the trip does not change on code red days for any option; (ii) reflects the assumption that people may expect other people to forego driving for riding public transit. Thus, traffic is expected to be lighter while transit becomes more crowded and uncomfortable; (iii) indicates that when air quality gets worse, people walking to and waiting at the bus stop are more exposed to ozone. Driving in a car may or may not increase risk while staying indoors is always safe; and (iv) implies that people are altruistic and may gain satisfaction (negative cost) for not driving on code red days or may feel guilty for driving. These relationships are sensible and not all are necessary for reaching the theoretical conclusion below.

Taking into account the cost changes on code red days, the change in the probability of driving (also taking transit and staying home) for an individual is ambiguous. This is mainly because declining air quality lowers the travel cost and health cost of driving *relative* to riding bus, although there may be some utility gain from reducing emissions. Even if people do not speculate about the improved traffic on code red days, or in some areas bus fares are waived for riders on high ozone days, which results in lower travel cost for riding bus, bus ridership may still not go up due to health concern about the air quality.

The above analysis shows that the voluntary information program does not provide people incentives necessarily consistent with reducing driving on code red days. It is important to empirically measure the impact of the program on driving amount.

3.4 Empirical Strategy

The primary question this study attempts to answer is whether the AQAD program changes individuals' travel behavior episodically. Do people reduce vehicle trips and/or miles traveled on code red days? Ideally, we would like to have a random sample of households in the Baltimore area, together with their daily VMTs for all summer days. However, such micro-data do not exist. What is available, instead, is data measuring traffic volumes during short time intervals on highways in the Baltimore area. (These will be described in detail in the next section). With these data, we can estimate the following model to measure changes in traffic on code red days that can be attributed to the AQAD program.

$$y_{it} = \gamma CRD_t + X_t B + \theta_i + \varepsilon_{it} \tag{3-3}$$

where y_{it} is (log) number of vehicles passing by traffic monitor i [20] on date t. CRD_t is an indicator for day t to be a code red day and the parameter γ measures the impact of code red day announcement on highway traffic volumes. The vector X_t contains other time varying factors that may affect vehicle trips, such as contemporaneous and lagged weather, the forecast 1-hour ozone concentration and observed ozone levels for the previous day, contemporaneous and lagged gas prices, public holiday dummies and a set of dummies for year, month, and day of the week. In a specification check, I include lagged traffic of the same time block on previous days and seven days ago. θ_i represents a monitor fixed effect to capture the time-invariant traffic characteristics for each monitor. The variable ε_{it} is an unobserved idiosyncratic term.

The problem in consistently estimating γ is that code red days are not random. Even conditional on all those covariates, there still could be some variables missing in the

[20] Please note this is different from the ozone monitoring stations mentioned earlier. Coincidentally, the number of traffic monitors in the sample is also seven.

model that are correlated with the code red day announcement and traffic flow. For instance, forecast weather plays a crucial role in predicting ozone concentration and determining code color. It is also arguably important in affecting people's travel decision for the coming day. However, historical forecast weather data is not readily accessible. Although we control for the observed weather and its lag, they may fail to account adequately for the forecast weather. If it is the case, a naïve regression estimation would yield a spurious estimate of γ.

However, if we could control for the conditional expectation of the unobservables in the model, we would still be able to estimate γ consistently. That is to estimate the following model instead of equation (3-3),

$$y_{it} = \gamma CRD_t + \lambda E\left(\varepsilon_{it} \mid CRD_t\right) + X_t B + \theta_i + \upsilon_{it} \tag{3-4}$$

where $E\left(\varepsilon_{it} \mid CRD_t\right)$ is expectation of ε_{it} conditional on the code red day indicator, and $\upsilon_{it} = y_{it} - E(y_{it} \mid CRD_t, X_t, \theta_i)$. If CRD_t is the only variable correlated with ε_{it}, OLS estimation of equation (3-4) yields a consistent γ estimate. In practice, $E\left(\varepsilon_{it} \mid CRD_t\right)$ is not observed. However, we know that the code red day announcement is completely dependent on the forecast ozone concentration, denoted by O. When and only when the forecast level exceeds a threshold, will it be a code red day. Formally,

$$CRD_t = f(O_t) = 1\{O_t >= O^*\}$$

where O^* denotes the threshold equal to 125 ppb . Thus, we could exploit the sharp regression discontinuity design (e.g. van der Klaauw 2002) to measure the impact of code red days. Since O, referred to as a running variable in the literature, captures all the information contained in CRD, $E\left(\varepsilon_{it} \mid CRD_t\right) = E(\varepsilon_{it} \mid O_t)$. Thus, we could estimate equation (3-5)

$$y_{it} = \gamma CRD_t + k(O_t) + X_t B + \theta_i + \upsilon_{it} \tag{3-5}$$

where $k(O)$ is a flexible functional specification for $E(\varepsilon \mid O)$. In the literature, $k(O)$ often takes the form of high-order polynomial series.

As noted above, the vector X contains a linear term in the forecast ozone level. It is, however, possible that the linear term is insufficient to completely account for the correlation between CRD and ε. Figure 3-1 illustrates that the estimates (γ') obtained by controlling only for the linear term in the forecast ozone level will underestimate (left panel) or overestimate (right panel) the true effect when the correlation between CRD and ε is a nonlinear function of O. In the estimation, I include up to a fifth order polynomial in the ozone forecast.

Two key assumptions must be satisfied in order to apply the regression discontinuity method (Imbens and Lemieux 2008). First, it is assumed that there is no manipulation of the running variable. In our case, if the expert panel adjusts the forecast ozone level to move a day into or out of the code red category based on expected transportation volumes, concern about the validity of RD strategy might be raised. A communication from one of the panel members stated that no sophisticated traffic information (e.g., forecasted daily traffic volumes) beyond the day of the week was considered in forecasting ozone concentration. More specifically, it happened occasionally that the forecast level was adjusted upward for Monday or downward for Friday based on the general impression about traffic patterns on these days. However, this is the only channel through which traffic is taken into account in code red day classification. In the next section, it is shown that Mondays and Fridays are not statistically more likely to be (or not be) a code red day. In addition, all models are estimated controlling for day-of-week dummy. In the robustness check, I exclude Mondays and Fridays from the sample used for estimation.

The other assumption underlying the RD model is that the unobserved variables that may affect traffic volumes evolve continuously at the cutoff point, i.e.125 ppb. This assumption cannot be verified directly. As a specification test presented in the next section, I check the discontinuity of the control variables, especially weather covariates. If some variables are found discontinuous at 125 ppb, it casts doubt on the continuity assumption for the unobservables.

3.5 Data

The Maryland Department of Environment (MDE) has archived the forecast and observed daily maximum one-hour ozone concentrations for the Baltimore area. I use data from May through mid-September --- the ozone season when the AQAD program is in place --- from 2001 to 2003. I focus on these three years because traffic data is available from 2001 and the color code assignment started to be based on an 8-hour ozone forecast and the 8-hour standard in 2004.[21] The code color is also available from

[21] The 8-hour standard is stricter in the sense that more days are designated as exceedance days. However, most exceedance days are code orange. It may be interesting to examine how the scheme change affects people's responses.

MDE. Alternatively, it can be determined by applying the rule described in Table 3-1. The latter matches the recorded one perfectly, which confirms the relationship between code color and forecast ozone. A sharp RD rather than fuzzy RD model is therefore appropriate.

In the early 2000s, the Maryland State High Administration (SHA) started to install detectors[22] along major roads to monitor and record traffic conditions. The detectors count the number of vehicles and volume is reported in five-minute intervals. For the project, weekday traffic volumes of the years 2001 through 2003 were obtained from the University of Maryland's Center for Advanced Transportation Technology Laboratory (CATT Lab), which archives data from the Maryland SHA.

As the detector system was established shortly before the period we examine, the performance of detectors and the data transfer network was not ideal. This resulted in considerable missing data. I restrict the set of detectors to be analyzed to those with less than 30 percent of 5-minute intervals missing, which gives seven detectors located on four major interstate highways in the Baltimore metropolitan area.[23] Table 3-2 provides information about the detectors and the traffic they are monitoring. The routes where these detectors are located all carry heavy traffic from the surrounding areas into and out of the Baltimore urban area. These roads rank from 3rd to 8th in terms of 2003 annual average daily traffic (AADT) in the area. Unfortunately, we do not have data for I-95 and

[22] Different from those buried underneath the road surface, this type of detectors is usually mounted on existing side-of-the-road poles and work with microwave sensor technology. See http://www.rtms-by-eis.com/rtms_features.html for more information.
[23] See Figure 3-2 for a map showing major freeways of the region and locations of detectors.

I-695, two major routes through and around the Baltimore area, respectively. Five detectors monitor inbound traffic while two monitor outbound traffic.

I aggregate the 5-minute volumes into four time blocks following the definitions in the Baltimore Metropolitan Council's travel demand model (BMC 2004). They are morning peak (6 AM – 10 AM), mid-day (10 AM – 3 PM), evening peak (3 PM – 7 PM), and other times (7 PM – 6 AM). This aggregation largely overcomes the short-term fluctuations in traffic flow caused by traffic conditions. More importantly, the time blocks group together hours with homogenous traffic patterns and separate those with different patterns. It is therefore more appropriate to study traffic pattern changes at the time block level than at 5-minute interval or hourly levels.

It is difficult to fill in missing observations on traffic volume. In general, filling in missing values of the dependent variable in a single-equation regression may lead to biased estimation (Greene 2003). So time blocks with one or more missing 5-minute interval are dropped from the regression. This may lead to an efficiency loss but should have no effect on estimator consistency so long as the time blocks that do not enter the volume regression are not systematically correlated with the explanatory variable of interest, i.e. *CRD*. Table 3-3 presents checks on the correlation between dropped time blocks and code red days. Each column represents a probit model specification with incremental inclusion of control variables. When *CRD* is the only explanatory variable (column (1)), it seems to affect the missing pattern of all times of day except for the morning peak period. However, since *CRD* occurs on hot, sunny days it may pick up weather impacts on the detector system. When the linear forecast ozone level and a full set of covariates including weather conditions are included (columns (2) and (3)) in the model, the effect of *CRD* becomes smaller and statistically insignificant. Adding polynomials terms in the forecast ozone level (column (4)) does not change the result at all. Thus, we conclude that estimating equation (3-5) with only the complete time blocks should not give us biased estimates due to missing observations.

Daily weather measures including temperature (maximum and minimum), wind speed, relative humidity (maximum and minimum) and precipitation were obtained from the National Climatic Data Center and are observed at the weather station located in the Baltimore-Washington International Airport. Daily average prices for regular unleaded gasoline in Baltimore area are provided by the GasBuddy Organization. I use the first through seventh lags of gasoline price to control for the impact of gas price on travel demand.

Columns (1) and (2) in Table 3-4 presents the means and standard deviations of control variables for non-code-red days and code red days, respectively. Column (3) shows differences in means between the two types of days and the associated standard errors. Generally speaking, a code red day is more likely to occur on hot, dry days with lower wind speed. The observed ozone level for the day before the forecasted day is significantly higher for the code red day. However, neither the short-term historical retail gas price nor the day of week differ significantly, which is consistent with the fact that the ozone forecasting model is basically a meteorological model rather than a behavioral one.

Although adjustments may have been made accounting for the day of the week, it seems to be a rare unsystematic practice.

One key identification assumption mentioned earlier is that the conditional mean of the unobservable, i.e. $E(\varepsilon \mid O)$, is continuous at O^* =125 ppb. The evidence in support of this assumption can be found by testing the continuity of the observed covariates. Figure 3-3 plots the average daily characteristics including temperature (max and min), precipitation, wind speed, humidity (max and min), retail gas price (lags), ozone observation (lag) and Monday and Friday dummies, against the forecast of ozone level. The predicted values from a fifth-order polynomial in the forecast level as well as the 95 percent confidence intervals are also presented. The figures suggest that there is no large, statistically significant break for these variables when ozone levels change from non-code-red days to code red days. Columns (4) and (5) of Table 3-4 provide quantitative support for this finding. Although code red days are different from non-code-red days, as shown in column (3), when the comparison is narrowed between code red days and code orange days in column (4), the difference diminishes dramatically in magnitude across all variables and only the max temperature and observed ozone level remain statistically significant. The higher max temperature and observed ozone level the day before most likely reflect only the higher forecast ozone level for code red days. Column (5), equivalent to Figure 3-3, reports the estimated coefficient of *CRD* when a fifth-order polynomial in forecast ozone level is included in the regression. It indicates that the difference between code red days and non-code-red days is small and statistically insignificant conditional on the forecast level. These results suggest that the unobserved characteristics are unlikely to be discontinuous at the CRD cutoff point.

3.6 Results

Table 3-5 presents the estimates of the effects of *CRD* on traffic volumes by time of day. Each model is estimated for a pooled sample as well as two sub-samples separating inbound detectors from outbound detectors. Although detector fixed effects account for the unique features of traffic pattern for each location and direction, it may be true that inbound and outbound traffic respond to *CRD* in distinct ways. Further, given symmetry between morning and evening travel, i.e. the morning inbound (outbound) traffic returns in the evening on the same routes, we should expect to see *CRD* have similar impacts on morning inbound (outbound) traffic and evening outbound (inbound) traffic. The sample is therefore split to explore the heterogeneity in the effects of *CRD* on inbound and outbound traffic. Common covariates across models include weather conditions and their lags, the observed ozone level for the previous day, lagged retail gas prices, and dummies for year, month, day of the week, public holidays and detectors.[24] Overall, the models explain traffic patterns reasonably well, with an R^2 above 0.90 for the full sample and above 0.80 for inbound and outbound sub-samples.

Columns (1)-(3) report the results of the first specification, in which the model controls for the ozone forecast in linear form only. For the full sample, *CRD* decreases morning peak traffic by 1.7 percent but increases mid-day traffic by 3.3 percent. The

[24] Models including lagged traffic on previous days and seven days ago yield no different estimates.

average weekday morning peak and mid-day traffic volumes across monitors are about 8500 and 8000, respectively. Applying the estimates suggests that on average 145 or so vehicle trips from 6 AM to 10 AM were cancelled or moved to other time periods. For the mid-day hours 10 AM to 3 PM, trips rose by about 264, which could be a result of trip rescheduling from the morning and/or people switching to driving to avoid ozone exposure. However, it is not obvious why people would postpone their vehicle travel closer to noon. When we look at inbound and outbound traffic separately, the *CRD* has little effect on inbound traffic except for increasing mid-day volumes by 4 percent. It lowers outbound traffic by 2.6 percent in the morning and 3.3 percent in the evening. These results are not consistent with a symmetric traffic pattern between inbound and outbound routes. As we discussed before, these estimates could be biased if the control function of the forecast level is not flexible enough.

Columns (4)-(6) are the baseline regression discontinuity models using a fifth order polynomial in forecast ozone to proxy for $E(\varepsilon \mid O)$. Column (4) shows that the *CRD* reduces morning traffic by 5 percent for the pooled sample, which is equal to about 425 vehicle trips on average. In contrast to column (2), the *CRD* does not exhibit a statistically significant impact on traffic during other periods of a day. When inbound and outbound traffic are examined separately (see columns (5) and (6)), the *CRD* is found to lower the morning peak inbound traffic by 5 percent. Moreover, this reduction is matched in the outbound traffic, which declines 2.6 percent in the evening peak and 5 percent in other hours on code red days. The coefficients of *CRD* are positive for the inbound sample during mid-day and evening and negative for morning outbound, but neither is statistically significant. These results suggest that the code red day alert indeed reduces traffic, albeit by a small proportion.[25]

Columns (7)-(9) maintain the RD specification and exclude the code green days from the sample, to test whether the results are driven by observations far away from the cutoff point.[26] The main finding remains unchanged: morning inbound traffic declines by 5 percent and the evening outbound traffic declines correspondingly. The difference is that outbound trip reductions are concentrated in the evening peak hours rather than in other hours. These estimates imply that the RD approach is appropriate for measuring the effect of the AQAD program, which a normal regression fails to capture.

Table 3-6 reports additional tests of the robustness of the results. The expert panel occasionally manipulates the ozone forecast and/or code color on Mondays and Fridays to account for traffic patterns, but not on other days of the week. The RD strategy is plausible if it yields similar estimates with a sample containing only Tuesday through Thursday. Columns (1)-(3) show that morning traffic is lower by 3 percent for the pooled sample and lower by 4 percent for the inbound sub-sample on code red days. Outbound traffic is reduced by 3 percent, though the effect is not statistically significant. Although

[25] Table A3 provides full estimation results for models specified in columns (4) through (6) of Table 3-5.
[26] Table 3-1 shows that code green days account for 51 percent of sample days and code yellow days account for 31 percent. The estimates appear to be sensitive to individual observations when code yellow days are removed. It is more likely because of the dramatic decrease in sample size.

the samples diminish in size by two fifths, we still find evidence consistent with the baseline results

Another test of the findings is to see whether similar reductions occur on other days, Code orange days mean an air quality alert to the public, although not to the same degree as on a code red day. Therefore, we expect no or a smaller decline in vehicle trips on code orange days. The hypothesis is tested in two specifications. I replace the *CRD* dummy with a dummy for code orange *and* code red days in the first case, and use two dummies, one for code orange days and one for code red days, in the second case. Columns (4)-(6) of Table 3-6 report the first specification and columns (7)-(9) report the second. The dummy for code orange and red days does not have a negative impact on traffic volumes. Instead, it increases the morning inbound traffic slightly. When models include two separate dummies, the code red dummy has significant negative effects on morning inbound volumes while the code orange dummy has statistically insignificant effects sometimes opposite to code red. Both results suggest that drivers do not respond to code orange as they do to code red days.

Code red days often occur on consecutive days. The cost of foregoing driving may rise on the second or third code red day. For instance, it may be easier for a professional to work from home one day a week than two or three days a week. On the other hand, if the marginal cost of driving on code red days increases, an individual is more likely to take some action on the second or third code red day than on the first. I estimate the following models to see the effect of consecutive code red days. In addition to the code red day dummy, I add to the model a dummy equal to one if it is the second, third or fourth (the longest string is four).code red day in a row, or a dummy for the third or fourth code red day. Columns (1)-(3) and (4)-(6) of Table 3-7 report the results for these two cases respectively. For the pooled sample, morning traffic is lower by 6 percent on the first code red day but only 4 percent lower for the second, third or fourth code red day. When the sample is split between inbound and outbound detectors, however, the effect loses statistical significance. A dummy for the third or fourth code red days in a row does not exhibit reinforcing or offsetting effects either.

3.7 Discussion and Conclusion

The findings of this study are similar to those in Cutter and Neidell's (2007), which examines a similar program in the San Francisco Bay Area. Both results suggest that the voluntary information programs lead to a small reduction in vehicle trips and the effect most is concentrated in the morning peak period. The evidence that the reduction occurs for the morning inbound traffic and evening outbound traffic seems to provide additional support for the main results.

The timing of the effect suggests that it is commuting trips that are reduced. The workers who usually drive to work could potentially work at home or switch to other travel modes such as taking public transportation, walking/biking and carpooling on code red days. The former is especially likely since, according to the 2001 National Household Travel Survey, 7.7 percent of workers work at home at least one day every month and 4.7

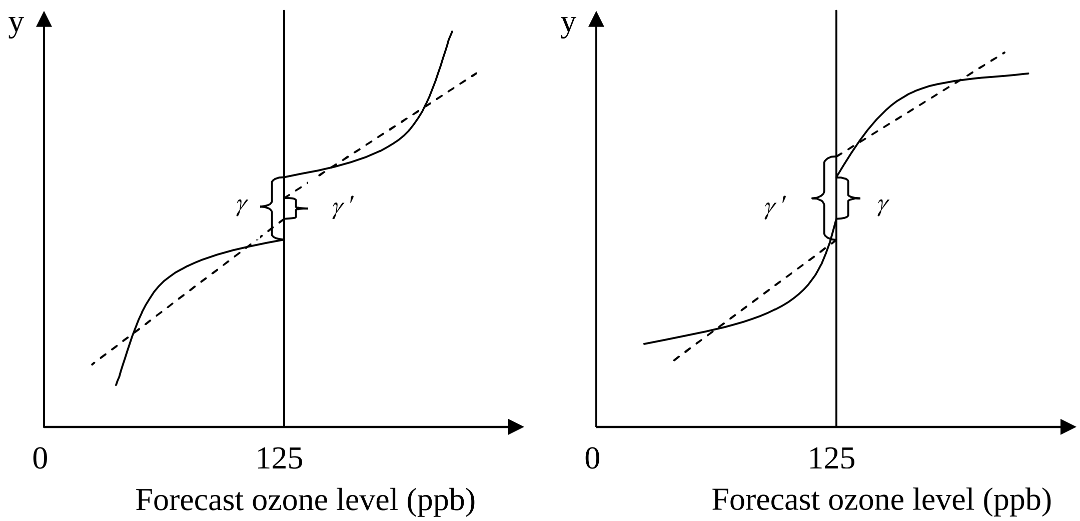
percent at least one day every week in the Washington-Baltimore metropolitan area. These people should generally have more flexibility to avoid driving on code red days.

Although the program is demonstrated to have some expected impact, the magnitude seems too small to reduce vehicle emissions dramatically. As the literature suggests voluntary programs are unlikely to improve air quality sufficiently to bring a region into compliance status. An innovative approach would be a permit program that restricts driving on high ozone days unless a permit is bought for each vehicle. The program could be effective if the permit price is set high enough, which presents a strong disincentive for many people to drive. Imposing the control on an episodic basis means the program could be more economically efficient than programs with year-round controls.

One objective of the programs like AQAD is to see how education and persuasion might alter individuals' behavior in favor of the environment. This study indicates that these efforts are not made in vain. In addition to limiting driving, the program also asks people to refuel vehicles after dusk or on another day. It may be worth investigating whether this is an easier behavioral change for people to make once data are available.

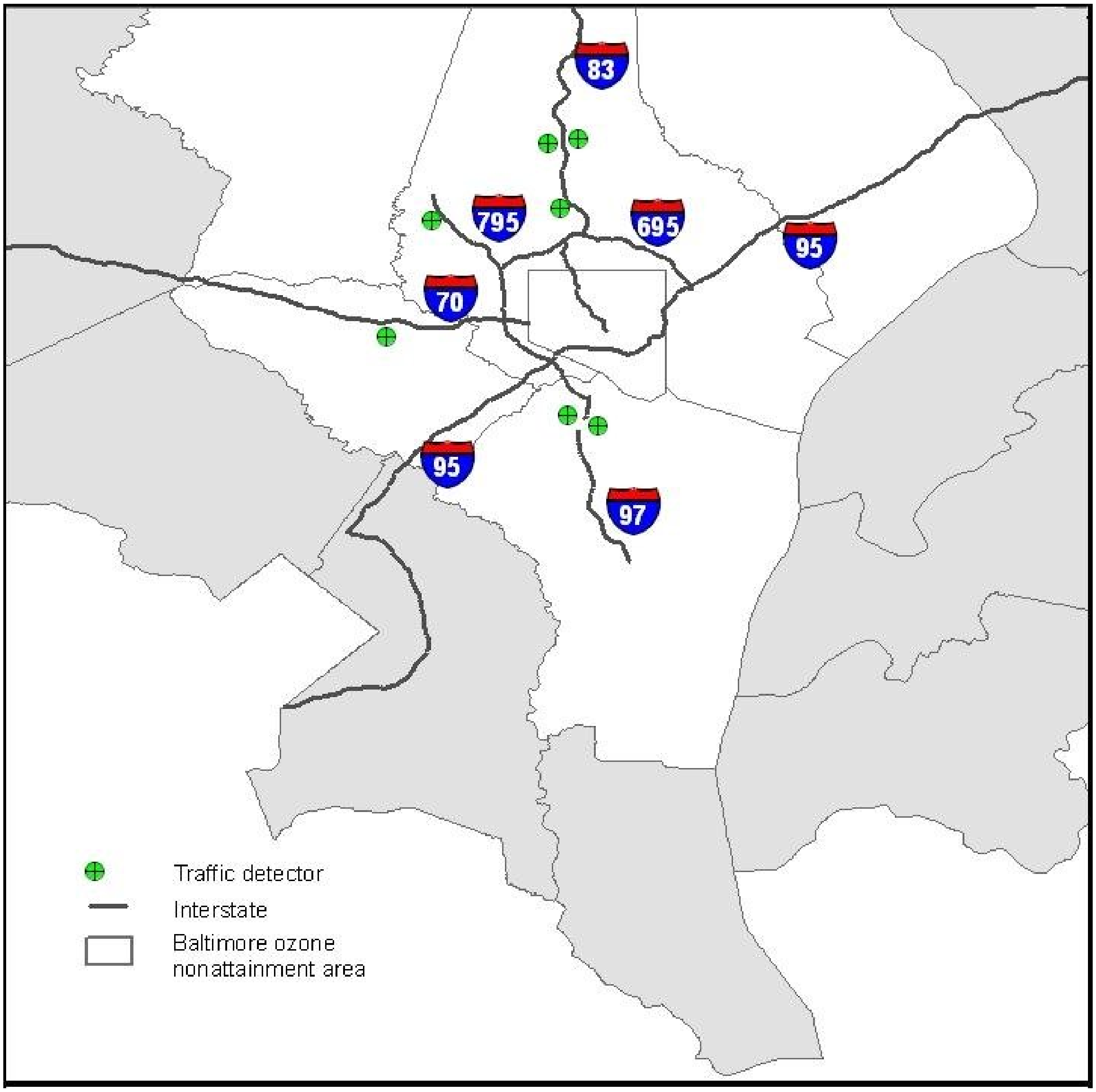
Figures and Tables for Chapter 3

Figure 3-1. Illustration of Biased Estimates with Linear Forecast Ozone Level



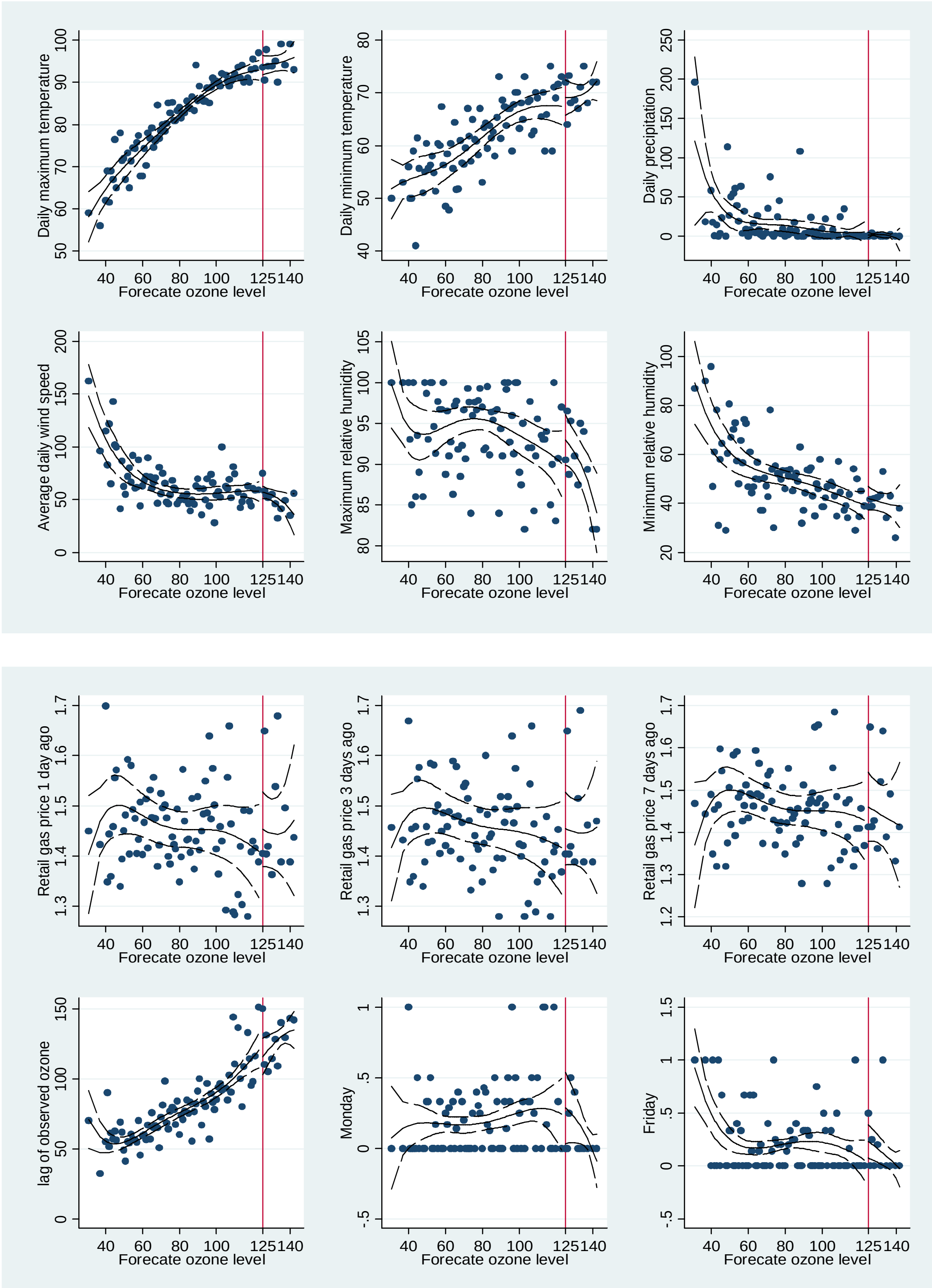
Note: The graphs show that the estimated *CRD* effect, γ', controlling for linear forecast ozone level could underestimate (left) or overestimate (right) the true effect of *CRD*, γ, when the underlying relationship between y and forecast ozone level is nonlinear.

Figure 3-2. Map of Baltimore Region Major Freeways and Maryland SHA's Traffic Detectors



Source: Created with ArcMap using Census 2000 TIGER/Line® Shapefiles and Bureau of Trasportation Statistics' Highway Performance Monitoring System data. Locations of detectors are not accurate but illustrative.

Figure 3-3. Similarity of Covariates around Code Red Day Cutoff Point



Note: The dots represent the average daily characteristics for each forecast ozone level. The continuous line is the predicted values from a fifth-order polynomial in forecast level with the dashed lines for 95 percent confidence interval.

Table 3-1. One-hour Ozone Level and Code Colors in Baltimore Area

1-hour Ozone (ppb)	Code Color	Health Concern	Number of Days 2001-2003
0 – 79	Green	Good	214
80 – 104	Yellow	Moderate	128
105 – 124	Orange	Unhealthy for sensitive groups	44
≥125	Red	Unhealthy	28

Source: http://www.mwcog.org/environment/air/downloads/calendar_2003.pdf, MWCOG.

Table 3-2. Description of Detectors and Traffic in Baltimore Area

Detector	Highway	AADT 2003	Direction	In/Out Bound	Missing %
1	I-83	86,293 (4th)	S	In	9.7
2	I-83	86,293 (4th)	S	In	26.3
3	I-83	86,293 (4th)	N	Out	18.5
4	I-795	81,500 (5th)	S	In	17.8
5	I-97	105,008 (3rd)	N	In	17.3
6	I-97	105,008 (3rd)	S	Out	9.4
7	I-70	44,142 (8th)	E	In	10.4

Note: The third column presents annual average daily traffic in 2003. The top two roads missing here are I-95 with AADT of 169,534 and I-695 with AADT of 167,473.

Table 3-3. Correlation between Missing Time Block and Code Red Day

	(1)	(2)	(3)	(4)
Morning peak	0.272	0.325	0.219	0.453
	(0.249)	(0.221)	(0.148)	(0.350)
	0.002	0.003	0.117	0.120
Mid-day	0.445	-0.068	-0.172	0.025
	(0.160)	(0.157)	(0.167)	(0.244)
	0.006	0.021	0.154	0.155
Evening peak	0.665	-0.064	-0.043	0.137
	(0.125)	(0.138)	(0.145)	(0.206)
	0.014	0.044	0.179	0.183
Other	0.349	0.300	0.142	0.218
	(0.179)	(0.174)	(0.176)	(0.237)
	0.004	0.004	0.088	0.089
N	2898	2884	2849	2849
Linear forecast ozone level	N	Y	Y	Y
2^{nd} to 5^{th} order polynomials of the forecast ozone	N	N	N	Y
Control variables	N	N	Y	Y

Note: Dependent variable is a binary indicator equal to 1 if the time block is to be dropped from traffic volume equation. The first row of each time-of-day panel is probit estimates of the coefficient of *CRD*, the second row is standard error clustered on each week, and the third row is the pseudo-*R* squared. Control variables include weather variables and their lags, observed ozone levels, lags of daily gas price, and year, month, day-of-week, holiday, and monitor dummies,.

Table 3-4. Summary Statistics and Difference in Selected Covariates Between Code Red Days and Other Days

	Non-CRD	CRD	CRD vs. Non-CRD	Orange vs. Red	Polynomials
	(1)	(2)	(3)	(4)	(5)
Max temperature	80.903	94.462	13.558	2.873	1.051
	8.771	3.313	(0.842)	(0.875)	(1.935)
Min temperature	60.824	69.538	8.714	2.480	1.630
	8.959	4.282	(1.002)	(1.347)	(2.826)
Precipitation	14.896	1.000	-13.896	3.412	-4.202
	39.252	2.966	(2.463)	(2.533)	(9.279)
Wind speed	62.654	52.654	-10	-5.434	-0.375
	25.356	12.103	(2.833)	(3.385)	(7.139)
Min relative humidity	51.639	40.846	-10.793	-1.624	3.273
	16.004	8.698	(1.965)	(2.246)	(4.974)
Max relative humidity	94.457	90.808	-3.650	-0.928	3.329
	6.794	6.487	(1.338)	(1.682)	(3.025)
Gas price 1 day ago	1.462	1.449	-0.013	0.021	0.048
	0.121	0.116	(0.024)	(0.034)	(0.063)
Gas price 3 days ago	1.464	1.45	-0.014	0.016	0.041
	0.121	0.107	(0.022)	(0.032)	(0.063)
Gas price 7 days ago	1.465	1.445	-0.020	0.002	0.036
	0.118	0.121	(0.025)	(0.033)	(0.066)
Ozone (lag)	75.526	123.654	48.128	17.595	-7.890
	23.293	20.829	(4.327)	(5.607)	(12.863)
Monday	0.197	0.192	-0.005	-0.102	0.063
	0.398	0.402	(0.082)	(0.112)	(0.245)
Friday	0.208	0.154	-0.054	0.007	0.200
	0.407	0.368	(0.076)	(0.095)	(0.154)
N	269	26	295	60	295

Note: Columns (1) and (2) are means and standard deviations (underneath) for non-code red days and code red days, respectively. Column (3) is the difference between CRD and non-CRD. Column (4) is the difference between CRD and code orange days. Column (5) is the estimate of CRD coefficient regressing each covariate on CRD and a fifth order polynomial in forecast ozone level. In the parentheses are standard errors. Those standard errors in the column (5) account for within-week clustering.

Table 3-5. Impact of Code Red Day Announcement on Traffic Volumes by Time of Day

	All	Inbound	Outbound	All	Inbound	Outbound	All	Inbound	Outbound
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Morning Peak									
Coefficient	-0.017**	-0.012	-0.026**	-0.051*	-0.051**	-0.034	-0.063*	-0.052*	0.008
Std. errors	(0.007)	(0.009)	(0.011)	(0.030)	(0.024)	(0.046)	(0.032)	(0.027)	(0.026)
N	1520	1059	461	1520	1059	461	736	517	219
R^2	0.96	0.97	0.96	0.96	0.97	0.96	0.97	0.98	0.97
Mid-day									
Coefficient	0.033*	0.039*	0.018	0.026	0.045	-0.006	-0.084*	-0.092	-0.02
Std. errors	(0.018)	(0.020)	(0.021)	(0.043)	(0.057)	(0.030)	(0.049)	(0.056)	(0.042)
N	1119	795	324	1119	795	324	485	360	125
R^2	0.93	0.94	0.87	0.93	0.94	0.87	0.96	0.96	0.93
Evening Peak									
Coefficient	-0.007	0.004	-0.033*	0.03	0.07	-0.026*	0.011	0.068	-0.069**
Std. errors	(0.02)	(0.026)	(0.017)	(0.059)	(0.093)	(0.014)	(0.102)	(0.164)	(0.029)
N	1157	787	370	1157	787	370	461	316	145
R^2	0.90	0.86	0.88	0.90	0.86	0.88	0.91	0.89	0.92
Other									
Coefficient	0.006	0.012	-0.013	-0.019	-0.01	-0.050*	0.009	0.018	-0.028
Std. errors	(0.012)	(0.011)	(0.018)	(0.019)	(0.018)	(0.027)	(0.027)	(0.026)	(0.049)
N	1201	839	362	1201	839	362	566	398	168
R^2	0.95	0.96	0.83	0.95	0.96	0.83	0.97	0.98	0.88

Note: Dependent variable is log of traffic volumes. Control variables include weather conditions and their lags, forecast 1-hour ozone concentration, observed ozone level for the day before, lagged retail gas prices, and dummies for year, month, day of the week, public holiday and monitor. Columns (1)-(3) control for linear ozone forecast only. Columns (4)-(9) control for a fifth-order polynomial in ozone forecast. Columns (7)-(9) focus on a sub-sample excluding code green days. Standard errors account for within-week clustering. * indicates significance at 10 percent level while ** at 5 percent level.

Table 3-6. Robustness Check

	All	Inbound	Outbound	All	Inbound	Outbound	All	Inbound	Outbound
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Morning Peak									
Code orange or both				0.019	0.036*	-0.003	0.005	0.025	-0.016
				(0.02)	(0.021)	(0.025)	(0.014)	(0.018)	(0.019)
Code red day	-0.028*	-0.037*	-0.018				-0.049*	-0.038**	-0.042
	(0.015)	(0.019)	(0.026)				(0.026)	(0.019)	(0.043)
N	903	627	276	1520	1059	461	1520	1059	461
R^2	0.98	0.98	0.99	0.96	0.97	0.96	0.96	0.97	0.96
Mid-day									
Code orange or both				-0.017	-0.025	-0.003	-0.011	-0.013	-0.006
				(0.027)	(0.035)	(0.028)	(0.030)	(0.037)	(0.033)
Code red day	-0.001	0.006	0.002				0.02	0.038	-0.009
	(0.059)	(0.080)	(0.040)				(0.047)	(0.063)	(0.035)
N	669	473	196	1119	795	324	1119	795	324
R^2	0.94	0.94	0.90	0.93	0.94	0.87	0.93	0.94	0.87
Evening Peak									
Code orange or both				-0.024	-0.053	0.019	-0.018	-0.039	0.012
				(0.032)	(0.044)	(0.016)	(0.040)	(0.057)	(0.017)
Code red day	0.053	0.123	-0.032				0.019	0.047	-0.019
	(0.114)	(0.188)	(0.020)				(0.070)	(0.110)	(0.014)
N	679	459	220	1157	787	370	1157	787	370
R^2	0.92	0.90	0.60	0.90	0.86	0.88	0.90	0.86	0.88
Other									
Code orange or both				0.016	0.02	0.021	0.013	0.02	0.007
				(0.014)	(0.014)	(0.022)	(0.014)	(0.015)	(0.025)
Code red day	0.030	0.023	0.029				-0.012	0	-0.046
	(0.028)	(0.029)	(0.046)				(0.020)	(0.019)	(0.032)
N	718	506	212	1201	839	362	1201	839	362
R^2	0.96	0.97	0.64	0.95	0.96	0.83	0.95	0.96	0.83

Note: Dependent variable is log of traffic volumes. Columns (1)-(3) use samples excluding Monday and Friday. Columns (4)-(6) replace the *CRD* dummy with a code-red-or-orange dummy. Columns (7)-(9) add a code-orange dummy in addition to the *CRD* dummy. Standard errors account for within-week clustering. * indicates significance at 10 percent level while ** at 5 percent level.

Table 3-7. Impact of *CRD*s in Sequence on Traffic Volumes by Time of Day

	All	Inbound	Outbound	All	Inbound	Outbound
	(1)	(2)	(3)	(4)	(5)	(6)
Morning Peak						
Code red days	-0.057*	-0.058**	-0.034	-0.054*	-0.051**	-0.035
	(0.030)	(0.024)	(0.047)	(0.028)	(0.022)	(0.047)
*CRD*s in Seq.	0.013*	0.015	0.001	0.006	-0.001	0.002
	(0.007)	(0.010)	(0.009)	(0.007)	(0.010)	(0.010)
N	1520	1059	461	1520	1059	461
R^2	0.96	0.97	0.96	0.96	0.97	0.96
Mid-day						
Code red days	0.020	0.040	-0.009	0.011	0.029	-0.009
	(0.042)	(0.056)	(0.028)	(0.039)	(0.053)	(0.026)
*CRD*s in Seq.	0.015	0.015	0.006	0.043	0.049	0.007
	(0.035)	(0.044)	(0.016)	(0.029)	(0.034)	(0.028)
N	1119	795	324	1119	795	324
R^2	0.93	0.94	0.87	0.93	0.94	0.87
Evening Peak						
Code red days	0.020	0.056	-0.029	0.045	0.094	-0.033**
	(0.047)	(0.072)	(0.019)	(0.062)	(0.098)	(0.016)
*CRD*s in Seq.	0.017	0.024	0.005	-0.035	-0.054	0.017
	(0.030)	(0.047)	(0.021)	(0.023)	(0.033)	(0.021)
N	1157	787	370	1157	787	370
R^2	0.90	0.86	0.88	0.90	0.86	0.88
Other						
Code red days	-0.011	-0.002	-0.043	-0.016	-0.006	-0.045*
	(0.023)	(0.024)	(0.029)	(0.022)	(0.023)	(0.027)
*CRD*s in Seq.	-0.017	-0.021	-0.014	-0.008	-0.011	-0.014
	(0.020)	(0.019)	(0.025)	(0.023)	(0.025)	(0.025)
N	1201	839	362	1201	839	362
R^2	0.95	0.96	0.83	0.95	0.96	0.83

Note: Dependent variable is log of traffic volumes. Columns (1)-(3) has one additional dummy equal to one if the code red day is the second, third or fourth one in a row. Columns (4)-(6) has a dummy equal to one if the code red day is the third or fourth one in a row. Standard errors account for within-week clustering. * indicates significance at 10 percent level while ** at 5 percent level.

4 Concluding Comments

4.1 Summary of Results

Chapter 2 calculates the percent of workers who use the Internet when working at home in a person's two-digit occupation by city size cell to instrument for telecommuting choice. After controlling for occupation and city fixed effects, as well as individual and household characteristics, this variable still predicts men and married women's probability to telecommute: a 10 percentage point increase in the internet penetration causes telecommuting probability to rise by 5 percentage points for married women and 3 percentage points for men.

Using this variable to instrument for telecommuting choice yields IV estimates that telecommuting leads a married women's one-way commute time to increase by 9 to 12 minutes. The effect on men's commute length is smaller, at about 5 minutes and statistically indistinguishable from zero. The results are robust for different specifications and sub-samples. Contrary to the OLS estimates, IV estimation finds that probability of commuting by driving does not decline due to telecommuting. For the average married female worker who commutes 24 minutes one way five days a week, telecommuting lowers weekly total commute time from 240 minutes to 198 minutes if the woman telecommutes two days a week. This means a 17 percent reduction, less proportional to the reduction in commuting frequency.

Chapter 3 finds that the code red day announcement results in a 4-5 percent reduction in vehicle commute trips in morning peak hours. However, this estimate is obtained only when we include in the regression a flexible function of forecast ozone levels, which is designed to control for the correlation between the code red day indicator and any non-random unobservables. If only the linear term of forecast ozone level is controlled in the regression, the estimate is as small as 1.7 percent. The difference highlights the importance of the identification strategy used.

The conclusion from these results is that the two TDM strategies work to some degree. Telecommuting is not shown to have a rebound effect on men's commute length. For married women, the effect seems moderate enough to result in a net reduction in commute miles. Consistent with findings in northern California, information about bad air quality could induce a small proportion of people to refrain from driving. It is more likely that these people will work from home rather than to switch to another travel mode. The effect, however, is not large enough to cause air quality improvements.

4.2 Directions for Future Research

Some questions related this dissertation remain unsolved. The instrumental variable developed in Chapter 2 does not have much power in explaining single women's telecommuting choices. Thus, the analysis cannot provide information about the responses of single females to telecommuting.

Commuting length reflects both residential location choice and work location choice. Telecommuters who choose longer one-way commute distances could choose to live farther from work or to work farther from home. It is important to distinguish the two possibilities from a public policy perspective.

For a two-earner household, housing location is determined jointly by both husband's and wife's employment locations. A change in one person's commuting cost might lead to changes in the commute lengths of both people. In this case, the sum of commute lengths of the household would be be the variable of interest. More research is needed to understand the impact of household members' telecommuting on total household commute length.

A natural extension of Chapter 3 is to apply the same technique to similar programs that have free bus fares. Free bus fares decrease the cost of riding a bus. However, for people who are used to driving, a larger share of the cost of switching to transit is the time and inconvenience to get on a bus. Moreover, it is of interest to know whether such a program passes the cost-benefit test. The voluntary program takes an episodic approach to controlling ozone, which is valuable in designing a pricing control scheme. Since ozone episodes occur only on hot, sunny days, the government could set a price for driving on those days. Daily automobile travel and resultant emissions could be managed by choosing a permit price. The cost-effectiveness of such a program if implemented in the Washington metropolitan area is being evaluated in an ongoing project.

Finally, economists may not want to give up the idea of managing travel demand via non-pricing strategies. Many TDM strategies may be effective in various contexts and even cost-effective if the political costs of pricing strategies are taken into account. Clearly, economists should participate in the design and evaluation of the TDM programs.

Appendices

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

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

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

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

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

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 $\Pr(x \ge t) = (b/t)^a$. 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

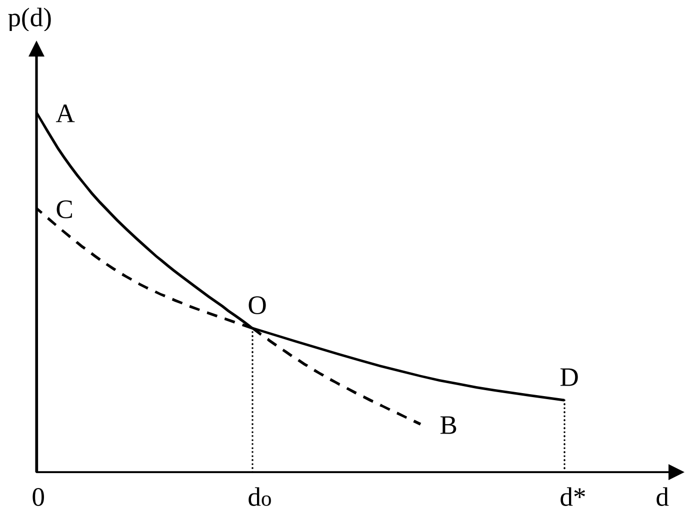


Table A1. CPS and NHTS Sample Construction

	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.

Table A2. Distributions by Commute Mode across Cities

Commute mode	Driving	Rail	Bus
Nationwide cities with 1 million or more population	0.878	0.044	0.463
Atlanta, GA	0.964	0.002	0.013
Baltimore, MD	0.883	0.032	0.053
Chicago-Gary-Kenosha, IL-IN-WI	0.819	0.112	0.034
San Francisco-Oakland-San Jose, CA	0.822	0.041	0.071
Washington DC-VA-MD-WV	0.831	0.072	0.064

Source: Author’s calculation using NHTS 2001. Commute mode is defined as transportation mode to work last week covering most of the distance.

Table A3. Full Results of Regression Discontinuity Models (Code red day coefficients correspond to Columns (4)-(6) in Table 3-5)

	All				Inbound				Outbound			
	Morning	Mid-day	Evening	Other	Morning	Mid-day	Evening	Other	Morning	Mid-day	Evening	Other
Ozone forecast	-0.016	-0.009	0.083	-0.036	-0.032	-0.013	0.151	-0.037	0.020	0.030	-0.032	-0.030
	(0.052)	(0.058)	(0.064)	(0.027)	(0.049)	(0.079)	(0.091)	(0.027)	(0.067)	(0.033)	(0.037)	(0.041)
2^{nd} order forecast	0.001	0.000	-0.002	0.001	0.001	0.001	-0.004	0.001	-0.000	-0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
3^{rd} order forecast	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
4^{th} order forecast	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
5^{th} order forecast	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag observed ozone	-0.000**	0.000	0.001**	0.000	-0.000*	0.000	0.001*	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. wind speed	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Min. humidity	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Max. humidity	0.001*	0.000	0.001	0.001	0.001	0.000	0.001	0.000	0.001	-0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Max. temperature	-0.001	-0.003**	-0.005***	-0.001	-0.001*	-0.005***	-0.007**	-0.001	0.000	0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Min temperature	-0.002**	-0.001	-0.000	-0.001	-0.002*	-0.001	-0.001	-0.001	-0.001	-0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.000***	0.000	0.000	-0.000	-0.000***	0.000	0.000	-0.000	-0.000***	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag avg. wind spd.	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag min. humidity	-0.001**	-0.000	-0.001	-0.001	-0.001**	-0.001	-0.001	-0.000	-0.000	0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Lag max. humidity	0.001*	0.000	0.000	0.001	0.001*	0.001	0.000	0.001	0.001	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)

Lag max. temp.	-0.000	-0.001	-0.005**	-0.001	-0.000	-0.001	-0.006**	-0.001	0.000	0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Lag min. temp.	0.000	0.002**	0.004***	0.001	0.001	0.003**	0.006***	0.001*	-0.000	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag precipitation	-0.000	-0.000	0.000	0.000	-0.000**	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lag gas price	-0.078	-0.109	0.108	-0.008	-0.081	-0.155	0.115	-0.004	-0.038	-0.074	0.024	-0.063
	(0.052)	(0.099)	(0.180)	(0.086)	(0.050)	(0.124)	(0.257)	(0.088)	(0.087)	(0.109)	(0.058)	(0.101)
2nd lag gas price	0.030	0.081	-0.071	0.160	0.059	0.091	-0.017	0.172	-0.040	0.119	-0.051	0.150
	(0.066)	(0.108)	(0.162)	(0.118)	(0.060)	(0.140)	(0.230)	(0.116)	(0.131)	(0.074)	(0.046)	(0.131)
3rd lag gas price	-0.012	-0.126	-0.202	-0.087	-0.014	-0.151	-0.373	-0.103	0.103	-0.039	-0.081	0.003
	(0.100)	(0.122)	(0.168)	(0.122)	(0.082)	(0.155)	(0.235)	(0.123)	(0.109)	(0.091)	(0.097)	(0.123)
4th lag gas price	0.073	0.109	-0.034	-0.005	-0.036	0.206	0.005	-0.011	0.088	-0.046	-0.007	0.001
	(0.116)	(0.118)	(0.150)	(0.116)	(0.085)	(0.160)	(0.213)	(0.123)	(0.092)	(0.121)	(0.118)	(0.151)
5th lag gas price	-0.173	-0.194*	0.153	-0.082	-0.172	-0.203	0.212	-0.062	-0.108	-0.235*	0.089	-0.181
	(0.128)	(0.114)	(0.150)	(0.116)	(0.145)	(0.128)	(0.238)	(0.113)	(0.125)	(0.135)	(0.098)	(0.171)
6th lag gas price	0.052	0.033	0.251	0.111	0.065	-0.095	0.340	0.099	-0.015	0.220	-0.001	0.189
	(0.124)	(0.138)	(0.204)	(0.138)	(0.144)	(0.156)	(0.277)	(0.140)	(0.100)	(0.261)	(0.087)	(0.195)
7th lag gas price	0.081	0.190*	-0.108	-0.076	0.152*	0.299**	-0.152	-0.082	-0.015	0.019	0.041	-0.087
	(0.065)	(0.097)	(0.140)	(0.065)	(0.078)	(0.126)	(0.181)	(0.087)	(0.074)	(0.171)	(0.085)	(0.089)
Year 2002	0.012	0.020**	0.008	0.019	0.011	0.013	-0.001	0.009	0.017*	0.045***	0.027**	0.036**
	(0.009)	(0.009)	(0.013)	(0.014)	(0.012)	(0.012)	(0.018)	(0.014)	(0.009)	(0.011)	(0.013)	(0.015)
Year 2003	0.052***	0.055***	0.016	0.052***	0.048***	0.053***	0.010	0.046***	0.055***	0.066***	0.039***	0.060***
	(0.007)	(0.009)	(0.012)	(0.011)	(0.008)	(0.012)	(0.019)	(0.011)	(0.008)	(0.008)	(0.008)	(0.013)
June	0.025**	-0.016	-0.072***	0.029**	0.014	-0.033*	-0.107***	0.031**	0.034**	0.022	0.001	0.030**
	(0.011)	(0.016)	(0.024)	(0.012)	(0.011)	(0.019)	(0.039)	(0.012)	(0.016)	(0.021)	(0.008)	(0.015)
July	0.022*	0.027**	-0.008	0.042***	0.001	0.012	-0.014	0.040***	0.050***	0.056***	0.001	0.049***
	(0.012)	(0.013)	(0.020)	(0.013)	(0.012)	(0.017)	(0.029)	(0.014)	(0.018)	(0.020)	(0.011)	(0.015)
August	0.029**	0.037***	0.015	0.047***	0.014	0.024	0.016	0.045***	0.045**	0.054**	0.019	0.052***
	(0.014)	(0.014)	(0.020)	(0.016)	(0.015)	(0.018)	(0.029)	(0.015)	(0.019)	(0.023)	(0.012)	(0.018)
September	0.004	-0.026**	0.009	-0.031*	0.013	-0.037**	0.012	-0.024	-0.019	-0.017	0.010	-0.041*
	(0.010)	(0.012)	(0.019)	(0.018)	(0.013)	(0.016)	(0.030)	(0.017)	(0.016)	(0.013)	(0.009)	(0.021)
Tuesday	0.019***	-0.007	0.003	0.034***	0.009*	-0.004	0.004	0.024***	0.033***	-0.013	0.012	0.055***
	(0.006)	(0.008)	(0.015)	(0.007)	(0.005)	(0.011)	(0.019)	(0.007)	(0.010)	(0.009)	(0.009)	(0.012)

Wednesday	0.030***	0.002	0.011	0.081***	0.015**	0.001	0.004	0.071***	0.055***	0.007	0.032***	0.107***
	(0.008)	(0.009)	(0.016)	(0.009)	(0.006)	(0.010)	(0.022)	(0.010)	(0.014)	(0.009)	(0.007)	(0.011)
Thursday	0.049***	0.020*	0.035**	0.131***	0.029***	0.007	0.029	0.109***	0.083***	0.055***	0.056***	0.179***
	(0.008)	(0.011)	(0.014)	(0.009)	(0.006)	(0.013)	(0.019)	(0.009)	(0.014)	(0.009)	(0.007)	(0.012)
Friday	0.033***	0.139***	0.099***	0.220***	-0.006	0.116***	0.113***	0.184***	0.111***	0.201***	0.075***	0.295***
	(0.008)	(0.013)	(0.016)	(0.012)	(0.008)	(0.013)	(0.022)	(0.012)	(0.014)	(0.014)	(0.008)	(0.014)
Public holiday	-1.202***	-0.097***	-0.375***	-0.119***	-1.365***	-0.084**	-0.237***	-0.090**	-0.896***	-0.120***	-0.652***	-0.183***
	(0.054)	(0.034)	(0.042)	(0.034)	(0.043)	(0.037)	(0.059)	(0.038)	(0.080)	(0.035)	(0.017)	(0.030)
Detector 2	1.480***	0.475***	0.101***	0.422***	1.479***	0.463***	0.096**	0.424***				
	(0.019)	(0.023)	(0.036)	(0.013)	(0.020)	(0.025)	(0.036)	(0.013)				
Detector 3	0.451***	0.599***	0.983***	0.494***					-0.801***		0.078***	-0.019***
	(0.014)	(0.018)	(0.030)	(0.011)					(0.010)		(0.006)	(0.005)
Detector 4	1.624***	0.994***	0.881***	0.750***	1.625***	0.995***	0.885***	0.752***				
	(0.014)	(0.018)	(0.033)	(0.009)	(0.014)	(0.018)	(0.034)	(0.010)				
Detector 5	1.427***	0.965***	0.859***	0.633***	1.427***	0.968***	0.867***	0.635***				
	(0.013)	(0.015)	(0.031)	(0.012)	(0.013)	(0.015)	(0.032)	(0.013)				
Detector 6	1.250***	0.841***	0.931***	0.514***						0.213***		
	(0.014)	(0.019)	(0.033)	(0.011)						(0.008)		
Detector 7	1.114***	0.160***	-0.045	-0.049***	1.114***	0.158***	-0.045	-0.047***				
	(0.018)	(0.017)	(0.029)	(0.012)	(0.018)	(0.017)	(0.029)	(0.012)				
Code red days	-0.051*	0.026	0.030	-0.019	-0.051**	0.045	0.070	-0.010	-0.034	-0.006	-0.026*	-0.050*
	(0.030)	(0.043)	(0.059)	(0.019)	(0.024)	(0.057)	(0.093)	(0.018)	(0.046)	(0.030)	(0.014)	(0.027)
Constant	8.050***	8.487***	7.485***	8.907***	8.347***	8.643***	6.551***	9.008***	8.620***	8.425***	9.807***	9.205***
	(0.702)	(0.804)	(0.891)	(0.427)	(0.675)	(1.091)	(1.242)	(0.418)	(0.903)	(0.455)	(0.553)	(0.630)
Observations	1520	1119	1157	1201	1059	795	787	839	461	324	370	362
R-squared	0.96	0.93	0.90	0.95	0.97	0.94	0.86	0.96	0.96	0.87	0.88	0.83

Standard errors in the parenthesis account for within-week clustering.* indicates significance at 10%; ** significant at 5%; *** significant at 1%

Bibliography

[1] Angrist, Joshua D., and Alan B. Krueger, 1992, “The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples”, *Journal of the American Statistical Association* 87, 328-336.

[2] Bloom, H. S., et al., 2004, “Baltimore Region Travel Demand Model for Base Year 2000”, Task Report 04-01, Baltimore Metropolitan Council.

[3] Bell, M. L., et al., 2004, “Ozone and Short-term Mortality in 95 US Urban Communities, 1987-2000”, *Journal of the American Medical Association*, 292, 2372-2378.

[4] Brueckner, Jan K., 2001, “Urban Sprawl: Lessons from Urban Economics”, in William G. Gale, and Janet Rothenberg Pack, eds.: *Brookings-Wharton Papers on Urban Affairs*, Brookings Institution Press.

[5] Crane, Randall, 1996, “The Influence of Uncertain Job Location on Urban Form and the Journey to Work”, *Journal of Urban Economics* 39, 342-356.

[6] Cutter, W. Bowman and Matthew Neidell, 2007, “Voluntary Information Programs and Environmental Regulation: Evidence from 'Spare the Air'”, Working paper.

[7] Cummings, R. G. and M. B. Walker, 2000, “Measuring the Effectiveness of Voluntary Emission Reduction Programmes”, *Applied Economics*, 32, 1719-1726.

[8] Dee, Thomas S., and William N. Evans, 2003, “Teen Drinking and Educational Attainment: Evidence from Two-Sample Instrumental Variables Estimates”, *Journal of Labor Economics* 21, 178-209.

[9] Drucker, Joshua, and Asad J. Khattak, 2000, “Propensity to Work from Home: Modeling Results from the 1995 Nationwide Personal Transportation Survey”, *Transportation Research Record* 1706, 108-117.

[10] Ellen, Ingrid Gould, and Katherine Hempstead, 2002, “Telecommuting and the Demand for Urban Living: A Preliminary Look at White-Collar Workers”, *Urban Studies* 39, 749-66.

[11] FCC, 2002, “Third Report on the Availability of High Speed and Advanced Telecommunications Capability”, Federal Communications Commission, Washington D.C.

[12] Fox, J. C. and M. Sarkar, 2002, “An Analysis of Air Pollution-Related Knowledge, Attitudes, and Behaviors across Time: the End of Season and Episodic Surveys”, MWCOG.

[13] Glaeser, Edward L., and Matthew E. Kahn, 2001, “Decentralized Employment and the Transformation of the American City”, *Brookings-Wharton Papers on Urban Affairs* 1-47.

[14] Greene, W. H., 2003, *Econometric Analysis*, 5th ed. Prentice Hall, New Jersey.

[15] Grubesic, Tony H., and Alan T. Murray, 2004, “Waiting for Broadband: Local Competition and the Spatial Distribution of Advanced Telecommunication Services in the United States”, *Growth and Change* 35, 139-165.

[16] Grubesic, Tony H., and Morton E. O'Kelly, 2002, “Using Points of Presence to Measure Accessibility to the Commercial Internet”, *Professional Geographer* 54, 259-278.

[17] Guimaraes, T., and P. Dallow, 1999, “Empirically testing the benefits, problems, and success factors for telecommuting programmes”, *European Journal of Information Systems* 8, 40-54.

[18] Hahn, J., P. Todd and W. van der Klaauw, 2001, “Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design,” *Econometrica,* 69(1), 201-09.

[19] Hausman, Jerry A., J. Gregory Sidak, and Hal J. Singer, 2001, “Cable Modems and DSL: Broadband Internet Access for Residential Customers”, *American Economic Review* 91, 302-307.

[20] Heckman, J., R. LaLonde and J. Smith, 1999, “The Economics and Econometrics of Active Labor Market Programs,” in Orley Ashenfelter and David Card, eds., *Handbook of Labor Economics, Volume 3A*, Section 7.4.6. Amsterdam: North-Holland.

[21] Henderson, Dennis K., and Patricia L. Mokhtarian, 1996, “Impacts of Center-Based Telecommuting on Travel and Emissions: Analysis of the Puget Sound Demonstration Project”, *Transportation Research: Part D: Transport and Environment* 1, 29-45.

[22] Henry, G. T. and C. S. Gordon, 2003, “Driving Less for Better Air: Impacts of a Public Information Campaign,” *Journal of Policy Analysis and Management*, 22(1), 45-63.

[23] Hensher, D. J., W. H. Greene, and J. M. Rose, 2005, *Applied Choice Analysis: a Primer*, Cambridge University Press.

[24] Imbens, Guido W., and Joshua D. Angrist, 1994, “Identification and Estimation of Local Average Treatment Effects”, *Econometrica* 62, 467-475.

[25] Imbens Guido W. and Thomas Lemieux, 2008, “Regression Discontinuity Designs: A Guide to Practice”, *Journal of Econometrics*, 142(2), 615-635.

[26] Inoue, Atsushi, and Gary Solon, 2005, “Two-Sample Instrumental Variables Estimators”, *NBER Working Paper* t0311.

[27] Kain, John F., 1968, “Housing Segregation, Negro Employment, and Metropolitan Decentralization”, *The Quarterly Journal of Economics* 82, 175-197.

[28] Kitamura, Ryuichi, Patricia Mokhtarian, Ram Pendyala, and Konstadinos Goulias, 1991, “An Evaluation of Telecommuting as a Trip Reduction Measure”, University of California Transportation Center, CA: University of California.

[29] Koening, Brett, Dennis Henderson, and Patricia Mokhtarian, 1996, “The Travel and Emissions Impacts of Telecommuting for the State of California Telecommuting Pilot Project”, *Transportation Research C* 4, 13-32.

[30] Krupnick, A. J., 1988, “Temporal and Spatial Control of Ambient Ozone”, Discussion Paper QE88-05, Resources for the Future, Washington DC.

[31] Kuzmyak, J. R. and Street Smarts, 2003, “Effectiveness of Free Bus Fares on Forecast Air Quality Code Red Days”, Interim Report for Northern Virginia Transportation Commission.

[32] Lee, D. S., E. Moretti, M. Butler, 2004, “Do Voters Affect or Elect Policies? Evidence from the U.S. House Election”, *Quarterly Journal of Economics,* 119, 807-859.

[33] Lomax, Tim, and David Schrank, 2005, “2005 Annual Urban Mobility Report”, Texas Transportation Institute, College Station, Texas.

[34] Lund, J. R., and P. L. Mokhtarian, 1994, “Telecommuting and Residential Location: Theory and Implications for Commute Travel in Monocentric Metropolis”, *Transportation Research Record* 1463, 10-14.

[35] Malecki, Edward J., 2002, “The Economic Geography of the Internet's Infrastructure”, *Economic Geography* 78, 399-424.

[36] Meyer, Peter B., and Anastasiya M. Osborne, 2005, “Proposed Category System for 1960-2000 Census Occupations”, *BLS Working Papers* 383.

[37] Mokhtarian, P. L., and I. Salomon, 1996, "Modeling the Choice of Telecommuting: 3. Identifying the Choice Set and Estimating Binary Choice Models for Technology-Based Alternatives", *Environment and Planning A* 28, 1877-94.

[38] Mokhtarian, Patricia L., Gustavo O. Collantes, and Carsten Gertz, 2004, "Telecommuting, Residential Location, and Commute-Distance Traveled: Evidence from State of California Employees", *Environment and Planning A* 36, 1877-97.

[39] Mokhtarian, Patricia L., Ilan Salomon, and Sangho Choo, 2005, "Measuring the Measurable: Why can't we Agree on the Number of Telecommuters in the U.S.?", *Quality and Quantity* 39, 423-452.

[40] MWCOG, 2005, Recommended Air Quality Forecast Procedures Baltimore-Washington Region.

[41] MWCOG, 2003, "2003 Air Pollution Episodic Surveys: Report of Findings for the Washington", DC and Baltimore Metropolitan Areas.

[42] Parry, Ian W. H., Margaret Walls, and Winston Harrington, 2007, "Automobile Externalities and Policies", *Journal of Economic Literature* XLV, 373-399.

[43] Plaut, Pnina O., 2006, "The Intra-Household Choices Regarding Commuting and Housing", *Transportation Research: Part A: Policy and Practice* 40, 561-571.

[44] Popuri, Y., and C. R. Bhat, 2003, "On Modeling Choice and Frequency of Home-Based Telecommuting", *Transportation Research Record* 1858, 55-60.

[45] Pratt, Joanne H., 2000, "Asking the Right Questions about Telecommuting: Avoiding Pitfalls in Surveying Home-based Work", *Transportation* 27, 99-116.

[46] Prystash, D. T., 1995, "Corporate attitudes and commitments to telecommuting", *Professional Communication, IEEE Transactions on* 38, 95-99.

[47] Small, Kenneth A., 1992a, "Trip Scheduling in Urban Transportation Analysis", *American Economic Review Papers and Proceedings*, 82(2), 482-486.

[48] Small, Kenneth A., 1992b, *Urban Transportation Economics*, Harwood, Philadelphia.

[49] Teller, A., 1967, "Air Pollution Abatement: Economic Rationality and Reality," *Daedalus*, 96, 1082-98.

[50] U.S. Environmental Protection Agency (EPA), 1993, "Automobiles and Ozone", 400/F-92-006 (January).

[51] _______, 1997, "Episodic Emission Control Programs", 420/F-97-022 (December).

[52] _______, 1999, "Smog: Who Does It Hurt?: What You Need To Know About Ozone and Your Health", EPA-452/K-99-001 (July).

[53] _______, 2003, "Ozone: Good Up High Bad Nearby", 451/K-03-001 (June).

[54] _______, 2004, "The Ozone Report: Measuring Progress through 2003", 454/K-04-001 (April).

[55] van der Klaauw, W., 2002, "Estimating the Effect of Financial Aid Offers on College Enrollment: A Regression-Discontinuity Approach," *International Economic Review*, 43(4), 1249-87.

[56] van Ommeren, Jos, Piet Rietveld, and Peter Nijkamp, 1997, "Commuting: In Search of Jobs and Residences", *Journal of Urban Economics* 42, 402-21.

[57] Walls, Margaret A., Elena A. Safirova, and Yi Jiang, 2007, "What Drives Telecommuting? The Relative Impact of Worker Demographics, Employer Characteristics, and Job Types", *Transportation Research Record*, No. 2010, 111-120.

[58] Walls, Margaret, and Elena Safirova, 2004, "A Review of the Literature on Telecommuting and Its Implications for Vehicle Travel and Emissions", Discussion Papers 04-44, Resources for the Future.

[59] Welch E., X. Gu, and L. Kramer, 2005, "The Effects of Ozone Action Day Public advisories on Train Ridership in Chicago", *Transportation Research Park D*, 10, 445-458.

[60] White, Michelle J., 1977, "A Model of Residential Location Choice and Commuting by Men and Women Workers", *Journal of Regional Science* 17, 41-52.

[61] White, Michelle J., 1986, "Sex Differences in Urban Commuting Patterns", *American Economic Review* 76, 368-72.

[62] White, Michelle J., 1988, "Location Choice and Commuting Behavior in

Cities with Decentralized Employment”, *Journal of Urban Economics* 24, 129-52.

[63] White, Michelle J., 1988, “Urban Commuting Journeys Are Not 'Wasteful'”, *Journal of Political Economy* 96, 1097-110.

[64] Wooldridge, J. M., 2001, *Econometric Analysis of Cross Section and Panel Data*, MIT press, Cambridge, MA.