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Analysis of telecommuting behavior and impacts on travel demand and the environment

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ABSTRACT

The discussion of whether, and to what extent, telecommuting can curb congestion in urban areas has spanned more than three decades. This study develops an integrated framework to provide the empirical evidence of the potential impacts of home-based telecommuting on travel behavior, network congestion, and air quality. In the first step, we estimate a telecommuting adoption model using a zero-inflated hierarchical ordered probit model to determine the factors associated with workers' propensity to adopt telecommuting. Second, we implement the estimated model in the POLARIS activity-based framework to simulate the potential changes in workers' activity-travel patterns and network congestion. Third, the MOVES mobile source emission simulator and Autonomie vehicle energy simulator are used to estimate the potential changes in vehicular emissions and fuel use in the network as a result of this policy. Different policy adoption scenarios are then tested in the proposed integrated platform. We found that compared to the current baseline situation where almost 12% of workers in Chicago region have flexible working time schedule, in the case when 50% of workers have flexible working time, telecommuting can reduce total daily vehicle miles traveled (VMT) and vehicle hours traveled (VHT) up to 0.69% and 2.09%, respectively. Considering the same comparison settings, this policy has the potential to reduce greenhouse gas and particulate matter emissions by up to 0.71% and 1.14%, respectively. In summary, our results endorse the fact that telecommuting policy has the potential to reduce network congestion and vehicular emissions specifically during rush hours.

1. Introduction

The transportation sector as the fastest growing energy end-use industry accounts for 27% of total U.S. greenhouse gas (GHG) emissions, making it the second largest contributor of U.S. GHG emissions (USEPA, 2016). Similarly, this sector accounts for more than 20% of total CO_2 emissions in the European Union countries (Eurostat, 2016). These rates are even more distinguishable in the countries where personal travel and goods movement are heavily relied on fossil fuels (Shaheen and Lipman, 2007). These trends along with the severe impacts of traffic-related air pollution on climate change and public health drive the need for effective congestion and pollution mitigation strategies.

The emergence of advanced mobility technologies such as alternative fuel vehicles (including electric and hydrogen vehicles) and

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hybrid vehicles can help to increase the fuel efficiency and reduce traffic-related emissions. While promising, these technologies have not yet reached their full potential and cannot yield substantial emission reductions in the short term (Amirgholy et al., 2017; Miralinaghi et al., 2017; Nichols et al., 2015). Mobility management strategies, on the other hand, have the potential to reduce travel demand and thereby traffic-related emissions in relatively short time horizons. Some examples of these policies are promoting the ridership of public transport, encouraging the use of shared mobility services (car-sharing, ride-sourcing, and bike-sharing), congestion pricing, and telecommuting.

Prior research has shown that among these policies, telecommuting imposes lower costs to the users and takes a shorter time to be implemented (Choo et al., 2005; Kim, 2017; Zhu and Mason, 2014). Telecommuters partially or entirely replace their out-of-home work activities by working at home or at locations close to home. In general, telecommuting offers more flexibility to workers by relaxing the temporal and spatial work-related constraints.

This policy has several potential benefits for both employers and employees. Firstly, it can improve telecommuters' family-work balance by providing more time for taking care of family members (Hilbrecht et al., 2008; Mokhtarian et al., 2004). Further, since telecommuters can travel during working hours on telecommuting days, they can plan more efficient activity-travel arrangements (Pendyala et al., 1991). In addition, previous research has shown that this policy can increase the employees' morale and productivity which significantly reduces organization costs in the long run (Bernardino, 2017). The increased productivity may be associated with multiple factors. In addition to the saved commuting time, it has been observed that telecommuters spend more time on work activities than they would in the workplace (Grawitch and Barber, 2010). Further, the flexible work schedule allows them to work during the hours when they are actually more productive, rather than the regular work hours (Kirk and Belovics, 2006).

On the other hand, since telecommuters have more flexibility to allocate time to various in-home or out-of-home activities during their working hours, they may decide to conduct additional trips and activities. This flexibility also opens up the opportunity of making more joint activities with other family members, such as leisure and recreational activities (Asgari et al., 2016; Golshani et al., 2018). Some studies have found empirical evidence of this travel-inducing effect, called rebound effect (see, for example, Koenig et al., 1996; Nilles, 1991; Zhu and Mason, 2014). In sum, the potential impacts of telecommuting are still debatable and empirical evidence on whether, and to what extent, telecommuting can improve traffic network congestion and traffic-induced emissions remains inconclusive.

Previous studies on telecommuting can be broadly categorized into two main streams. The first stream focuses on workers' telecommuting adoption behavior and aims to identify the factors associated with their propensity to adopt this policy. Some examples of this research direction include Alexander et al. (2010), Drucker and Khattak (2000), Mannering and Mokhtarian (1995), Mokhtarian and Salomon (1997), Sener and Bhat (2011), and Singh et al. (2013). The second group, on the other hand, investigates the potential consequences of this policy. Some examples of this research line which explore the impacts of telecommuting on travel-related decisions (e.g., mode choice and departure time choice) and network congestion measures (e.g., trip counts in the network and VMT) include Asgari and Jin (2017), Choo et al. (2005), Helminen and Ristimäki (2007), Lachapelle et al. (2017), Pendyala et al. (1991), and Zhu and Mason (2014). A detailed review of these studies can be found in "Literature review" section.

The current study brings together the two research areas by presenting a comprehensive telecommuting analysis which first, investigates workers' telecommuting adoption behavior and second, evaluate the consequences of this policy on travel behavior, network congestion, and air quality. The contribution of this study to the literature is threefold. First, we develop a home-based telecommuting participation and frequency model. In doing so, a zero-inflated hierarchical ordered probit model is set up and estimated using a revealed choice data obtained from the CMAP Travel Tracker Survey (CMAP, 2008). The rationale for adopting this method lies in the excessive number of non-telecommuters in the dataset, which is expected because many workers either do not have the option of telecommuting or they prefer not to telecommute even when it is a feasible option for them (Singh et al., 2013).

Second, we implement the estimated model in the POLARIS activity-based framework (Auld et al., 2016a) to simulate the potential impacts on workers' activity-travel behavior and network congestion. Activity-based models can provide more realistic and policy-sensitive simulation environments for assessing the potential effects of travel demand management (TDM) policies in general and telecommuting in specific. However, despite their great capability in simulating individuals' activity-travel behavior, studies that have focused on telecommuting and its implications for travel and the environment are still scarce. Third, the US DOE's Autonomie vehicle energy simulator and the US EPA's MOVES mobile source emission model are used to estimate potential changes in vehicular fuel use and emissions in the network as a result of telecommuting. The results of this study can shed light on understanding the true effects of this policy and offers a practical approach for testing potential effects of such TDM strategies.

The remainder of this article is structured as follows: In the next section, we briefly review the related studies on telecommuting behavior and integrated travel demand-emission frameworks. Then, descriptive analysis of the data used in this study is presented. In Section 4, we describe the structure of the telecommuting participation and frequency model, along with detailed estimation results and interpretation of model parameters. Section 5 elaborates on the integrated simulation platform, implementation of the estimated model, and simulation results. The paper concludes with a summary of the major findings and recommendations for future studies.

2. Literature review

2.1. Telecommuting behavior and implications

Telecommuting can entirely reshape workers' daily activity schedules. Therefore, to obtain an accurate representation of their activity planning and scheduling behavior, it is of great importance to account for their propensity to adopt telecommuting. Several studies have attempted to address this issue over the past few decades (see, for example, Drucker and Khattak, 2000; Mokhtarian and

Salomon, 1997; Paleti and Vukovic, 2017; Sener and Bhat, 2011; Singh et al., 2013). These studies mostly rely on statistical analysis of workers' decisions about choice and frequency of telecommuting, and aim to recognize the associations between their decisions and various types of personal, household, job-related, and built-environment attributes.

Early studies in this line of research date back to mid-1990s. They are mostly based on stated-preference (SP) surveys, because the low popularity of telecommuting at that time hindered the collection of revealed-preference (RP) data (see, for example, Bernardino et al., 1993; Sullivan et al., 1993). Later, by increasing the awareness about telecommuting and its potential benefits, large-scale RP surveys started to include questions regarding workers' perception of, and propensity towards this policy. Studies conducted by Drucker and Khattak (2000), Mannering and Mokhtarian (1995); Mokhtarian and Salomon (1997), and Olszewski and Mokhtarian (1994) are some examples of RP-based telecommuting adoption analyses.

More recent studies aimed at modeling the decisions on the adoption and frequency of telecommuting in a unified structure to capture the correlation between them. In this regard, Popuri and Bhat (2003) presented a joint discrete choice model of adoption and frequency of home-based telecommuting using a RP survey collected in the New York metropolitan region. They found a strong association between individuals' attributes, households' demographics, and work-related factors on the one hand, and telecommuting adoption and frequency decisions on the other hand. They also provided empirical evidence that failure to accommodate for common unobserved factors affecting the two decisions can lead to inconsistent parameter estimates. More recently, Sener and Bhat (2011) presented a copula-based joint model which incorporated a binary choice model to estimate the telecommuting choice, and an ordered-response model to estimate the frequency. In another study, Singh et al. (2013) incorporated the option of telecommuting as a supply-side factor and presented a joint trivariate model to estimate the option, choice, and frequency of telecommuting using the 2009 National Household Travel Survey dataset.

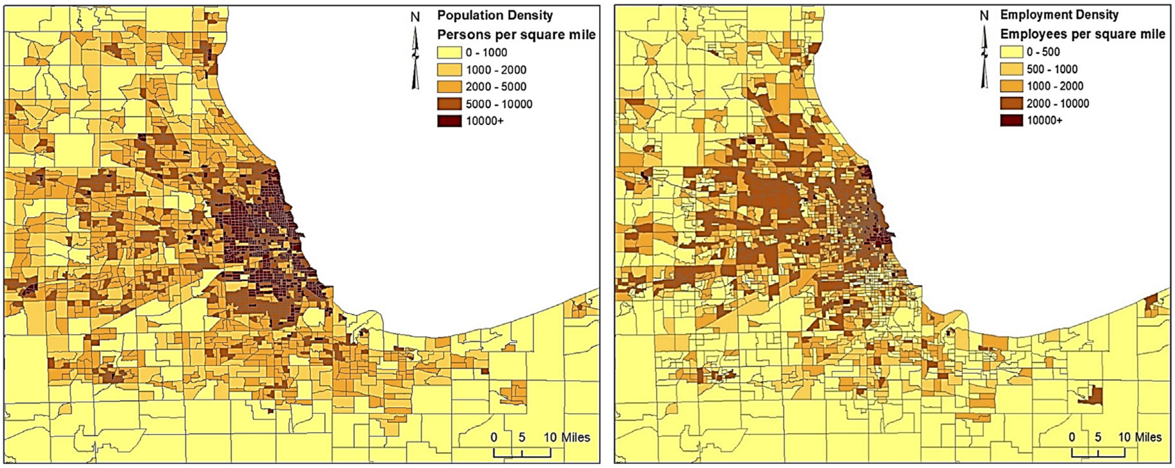
From another perspective, several studies have attempted to assess the impact of this policy on telecommuters' trip rates and miles driven. While it has been largely accepted that telecommuting reduces commute travel, there are conflicting viewpoints about its overall impact on workers' daily activity-travel behavior. Many studies have found results supporting the hypothesis that telecommuting can reduce daily trip rates, travel distance, and VMT. For example, based on a spatial and temporal analysis of travel diaries in California, Pendyala et al. (1991) found that this policy can reduce telecommuters' peak period trips by 60% and their total distance traveled by 75% on telecommuting days. In another study, Choo et al. (2005) studied the impact of telecommuting on VMT and reported that this policy can reduce annual VMT up to 0.8%. Comparing this result with approximate VMT reductions caused by public transit services, they concluded that telecommuting is a far more cost-effective congestion mitigation policy. Similarly, Helminen and Ristimäki (2007) found that home-based telecommuting in Finland can reduce the total commute distance by 0.7%, which would be equal to 0.84 million miles saved per week. More recently, Lachapelle et al. (2017) studied the impacts of telecommuting on travel time and peak hour travel in Canada Using time use data from the Canadian General Social Survey. The found that this policy can reduce daily travel time by an average of 13 min. They also found that as telecommuters have more flexible activity schedules, they mostly take trips during off-peak periods.

On the other hand, focusing on the complementary effects of telecommuting, few other studies have provided results indicating an increase in travel measures as a result of this policy (Koenig et al., 1996; Nilles, 1991; Zhu and Mason, 2014). In overall, the impacts of telecommuting on both travel demand and network operation are still inconclusive and there is substantial need for more empirical evidence on this issue (Kim, 2017; Zong et al., 2013).

2.2. Integrated travel demand-emission models

The interest in analyzing individuals' behavioral responses to TDM policies has led to a shift from aggregate trip-based models to disaggregate activity-based models. In such individual-level models, travel is considered as a demand derived from the need to pursue activities (Bowman and Ben-Akiva, 2001). Besides, ABMs focus on the sequence of activities and trips rather than individual trips so that they can capture the spatiotemporal linkages among them. In principle, the results of ABMs can be investigated at very fine scales of households or individuals, and the impact of various TDM policies can be appraised explicitly, rather than attempting to recover those effects from aggregate results. Some of the well-known and practical activity-based models are CEMDAP (Bhat et al., 2004), Albatross (Arentze and Timmermans, 2004), TASHA (Miller and Roorda, 2003), SimTRAVEL (Pendyala et al., 2012), ADAPTS (Auld and Mohammadian, 2012), and POLARIS (Auld et al., 2016a). For a detailed review of the research on activity-based travel demand modeling, the reader is referred to Castiglione et al. (2015) and Rasouli and Timmermans (2014).

As a potentially useful application of ABMs, several researchers have investigated their capability in air quality analysis against the use of a traditional four-step model. For example, Shiftan and Suhrbier (2002) integrated the Portland activity-based model and MOBILE5 emission model to explore the environmental impacts of congestion pricing and transit improvements. In another study, Hatzopoulou et al. (2011) integrated TASHA activity-based model with MATSim as the dynamic traffic simulator to simulate people's travel patterns in the network and input them into MOBILE and CALPUFF to estimate vehicle emissions and atmospheric dispersions. In a similar study, Dons et al. (2011) developed an integrated framework to estimate ambient pollutant concentrations by linking Albatross, MIMOSA emission model, and AURORA dispersion model. Similarly, Vallamsundar et al. (2016) integrated OpenAMOS activity-based model with MOVES emission model and AERMOD air dispersion model to estimate population exposure levels of fine particulate matter in Arizona. In a recent study, Shabanpour et al. (2017) integrated ADAPTS activity-based model with MOVES emission model and applied the proposed framework to assess the environmental impacts a large-scale and a small-scale transportation policy in Chicago region.



(a) (b)

Fig. 1. Distribution of calculated built-environment factors: (a) population density and (b) employment density in Chicago Metropolitan Area.

3. Data analysis

The data used in this study to analyze the telecommuting behavior is extracted from the Travel Tracker Survey conducted by the Chicago Metropolitan Agency for Planning (CMAP). The data includes complete travel information of 10,500 households who were asked to report their travel diary for one or two randomly assigned days between January 2007 and February 2008. It also contains a full set of individual and household demographic characteristics (e.g., age, gender, income, number of vehicles, residential location, etc.), trip-related information (mode, time-of-day, trip duration, etc.), and activity-related information (e.g., activity type and duration, location, etc.). Moreover, several land-use and built-environment measures such as population density, housing density, employment density, intersection density, and road density are calculated at the level of census tracts based on the available information about individuals' residential and work locations, and merged with the main dataset. Fig. 1 presents the spatial distribution of population and employment in the Chicago metropolitan area. Similar to other major metropolitan areas in the U.S., a significant portion of the population and employment are centered in the city area and their densities significantly decrease in the suburban areas; however, their patterns are dissimilar.

To analyze people's telecommuting behavior, we focus on employed individuals whose primary work location is outside home. After filtering the dataset, 7244 individuals remained for the analysis. The information for modeling the telecommuting behavior is obtained from the key question on frequency of telecommuting in the survey. This study considers five levels of (1) do not telecommute, (2) a few times a year, (3) once a month, (4) once a week, and (5) almost every day for estimating people's propensity to adopt telecommuting. Fig. 2 illustrates the distribution of telecommuting frequency in the dataset which implies the excessive number of non-telecommuters in the sample.

The descriptive analysis of the data reveals some interesting insights about people's telecommuting behavior. The analysis indicates that about 13% of men telecommute at least a few times a year while about 10% of women do so. Middle-aged individuals

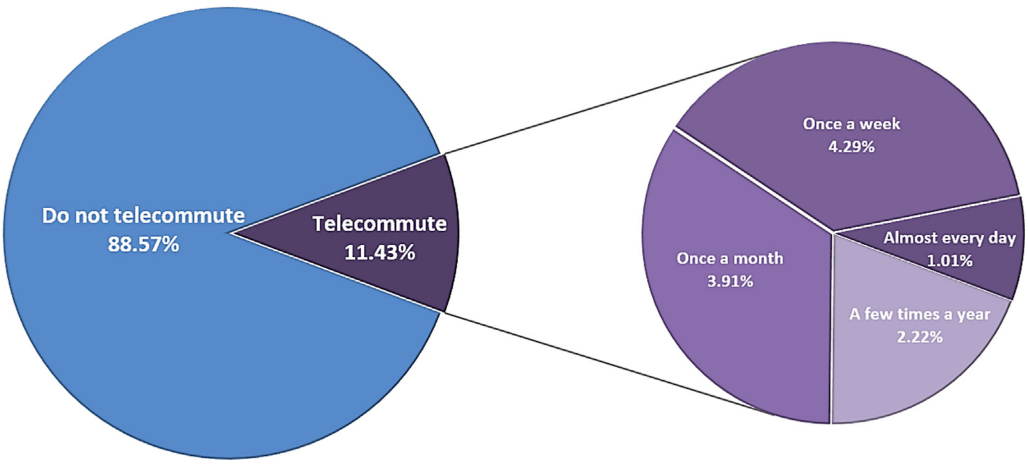


Fig. 2. Distribution of telecommuting frequency in the sample.

Table 1
Summary Statistics of the Key Variables Used in the Final Model.

Variables	Description	Mean	St. Dev.
Person demographics:			
Gender: male	1: if traveler is male; 0: o/w	0.53	0.50
Age: 35–55	1 if traveler is between 35 and 55 years old; 0 o/w	0.47	0.50
Income: low	1 if income is less than $50,000; 0 o/w	0.19	0.40
Income: med	1 if income is between $50,000 and $100,000; 0 o/w	0.21	0.40
Education: low	1 if traveler has high school or college/associate degrees; 0 o/w	0.34	0.47
Education: graduate	1 if traveler has a graduate degree; 0 o/w	0.27	0.45
Household characteristics:			
HH worker	Number of workers in the household	1.87	0.77
HH vehicle	Number of vehicles in the household	2.09	1.03
HH vehicle: high	1 if household has more than 2 vehicles; 0 o/w	0.27	0.45
Vehicle availability	1 if vehicle is available for work; 0 o/w	0.22	0.41
Trip information:			
Trip distance	Trip distance (mile)	10.19	9.82
Trip distance: high	1 if greater than 20 miles; 0 o/w	0.14	0.35
Trip duration	Trip duration (hour)	0.56	0.49
Job characteristics:			
Work flexibility	1 if traveler is free to adjust his/her schedule; 0 o/w	0.12	0.33
Work duration	Work duration (hour)	7.51	2.84
Occupation: transportation	1 if traveler is in transportation, utilities, or warehousing; 0 o/w	0.07	0.25
Occupation: management	1 if traveler is in management of companies or enterprises; 0 o/w	0.02	0.15
Occupation: health	1 if traveler is in health care or social assistance services; 0 o/w	0.13	0.33
Occupation: government	1 if traveler has a government job; 0 o/w	0.09	0.28
Occupation: communication	1 if traveler is in communication industry; 0 o/w	0.04	0.21
Occupation: manufacturing	1 if traveler is in manufacturing industry; 0 o/w	0.13	0.33
Built-environment factors:			
Employment density: high	1 if greater than 20,000 employees in the census tracts	0.16	0.36
Employment density: low	1 if less than 3000 employees in the census tracts	0.41	0.49
Population density	Population density/10,000 in census tract	0.67	0.96

(35–55 years old) have the highest rates of telecommuting – about 13%. We also found that education level positively affects the telecommuting propensity. Only 6% of individuals who have education level lower than bachelor's degree telecommute, while respectively about 14% and 18% of individuals with bachelors and graduate degrees telecommute at least a few times a year. Moreover, workers with higher income and those in communication and service industries telecommute more often than others. About 11% of workers with the income range of $50–$100k per year telecommute, while only 3% of the workers who make less than $50k per year telecommute at least a few times a year. Table 1 presents summary statistics for the key variables of the data that are used in this study.

4. Telecommuting participation and frequency

4.1. Model structure

Due to the ordinal nature of the five telecommuting frequency levels, this study applies a version of ordered probit model. Descriptive analysis of the data, however, reports the frequency of these five responses as 6416, 161, 283, 311, and 73, respectively. The spike at zeros (i.e., the do not telecommute response) shows the excessive number of non-telecommuters and suggests a type of latent class arrangement in the population. The excessive number of do not telecommute observations can be associated with the fact that many workers either do not have the option of telecommuting or they prefer not to telecommute even when it is a feasible option for them (Singh et al., 2013). To address this issue, we adopt an extended version of zero-inflated ordered probit (ZIOP) model (Greene and Hensher, 2010; Harris and Zhao, 2007) to estimate individuals' telecommuting choices.

This model splits the population into two regimes that their decision outcomes relate to potentially two different sets of explanatory variables. This modeling approach in the context of telecommuting can be interpreted as whether an individual has the option of telecommuting, and then, conditional on feasibility, how often he/she conducts telecommuting which also includes zero occurrence. Therefore, this model consists of two stages; the first stage (known as participation equation) deals with a binary choice of whether an individual is a "potential telecommuter" or not, which can be formulated as follows:

$$PT^{*} = \alpha z + \nu, \quad \nu \sim N[0,1] \tag{1}$$

$$PT = 1 \ if \ \ PT^{*} > 0, \quad 0 \text{ otherwise} \tag{2}$$

where PT^{*} is an unobserved variable used for modeling the Potential of Telecommuting (PT), z is the set of independent variables, α. is the vector of estimable parameters, ν is the stochastic random error term which is assumed to be normally distributed, and PT

corresponds to the binary choice of conducting telecommuting.

The second stage (known as activity equation) corresponds to the frequency of conducting telecommuting that is estimated with an ordered probit model as follows (Washington et al., 2010):

$$LT^{*} = \beta x + \varepsilon, \quad \varepsilon \sim N[0,1] \tag{3}$$

$$LT = j \text{ if } \mu_{j-1} < LT^{*} < \mu_j, \quad j = 0,1,...,J \tag{4}$$

here, LT^{*} is the unobserved latent variable that is used as the basis for modeling the Level of Telecommuting (LT), x is the vector of independent variables, β is the vector of estimable parameters, μ_j is the threshold that defines LT and is estimated jointly with β, LT corresponds to the integer ordering, j is the integer ordered choice for the dependent variable, and ε is the random error term assumed to be normally distributed and be independent of ν..

While PT and LT are not individually observable in terms of the zeros, they are observed via the criterion:

$$T = PT \cdot LT \tag{5}$$

That is, to observe the $T = 0$ outcome we require either $PT = 0$ (the individual is not a potential telecommuter), or $PT = 1$ and $LT = 0$ (although the individual is a potential telecommuter, he/she does not telecommute). Therefore, assuming that $\Phi_1(.)$ is the univariate cumulative normal distribution, the associated probabilities obtained from the binary probit model for choice of telecommuting and the ordered probit model for level of telecommuting can be written as:

$$\Pr(T = 0|x,z) = [1-\Phi_1(\alpha z)] + \Phi_1(\alpha z) * \Phi_1(0-\beta x) \tag{6}$$

$$\Pr(T = j|x,z) = \Phi_1(\alpha z) * [\Phi_1(\mu_j-\beta x)-\Phi_1(\mu_{j-1}-\beta x)] \tag{7}$$

Furthermore, the choice of telecommuting and the level of telecommuting could be correlated due to unobserved effects; thus, by imposing a bivariate normal distribution on the error terms of the two equations, we account for the unrestricted correlation (Greene and Hensher, 2010):

$$\begin{pmatrix} \nu \\ \varepsilon \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{8}$$

here, ρ ρ .is the correlation coefficient and needs to be estimated along with other estimable parameters. In this model known as zero-inflated ordered probit with correlated error terms (ZIOPC), the correlation coefficient in the modeling framework transforms the independent probability structures of the observed outcomes to a bivariate model as (Greene and Hensher, 2010):

$$\Pr(T = 0|x,z) = [1-\Phi_1(\alpha z)] + \Phi_2(\alpha z,-\beta x,-\rho) \tag{9}$$

$$\Pr(T = j|x,z) = \Phi_2(\alpha z,\mu_j-\beta x,-\rho)-\Phi_2(\alpha z,\mu_{j-1}-\beta x,-\rho) \tag{10}$$

where $\Phi_1(.)$ and $\Phi_2(.)$ are the univariate and bivariate cumulative normal distribution functions, respectively; μ_j and μ_{j-1} are the upper and lower thresholds of the outcome j, respectively. The log-likelihood function can then be written as:

$$\begin{aligned} \mathrm{LL}(\alpha,\beta,\mu) = \sum_{i=1}^{N}\sum_{j=0}^{J} \delta_{ij}\ln[Pr(T_i = j|z_i,x_i,\alpha,\beta,\mu)] = \sum_{i=1}^{N} \delta_{i0}\ln[[1-\Phi_1(\alpha z)] + \Phi_2(\alpha z,-\beta x,-\rho)] \\ + \sum_{i=1}^{N}\sum_{j=1}^{J} \delta_{ij}\ln[\Phi_2(\alpha z,\mu_j-\beta x,-\rho)-\Phi_2(\alpha z,\mu_{j-1}-\beta x,-\rho)] \end{aligned} \tag{11}$$

where, J is the total number of choices, and δ_{ij} is a binary variable indicating if person i chooses outcome j.

The mentioned ZIOPC model assumes that the same set of independent variables affect the probability of all outcomes. Moreover, the thresholds of ordered choices are assumed to be the same for all observations in the dataset. These assumptions limit the usefulness of such models in the sense that they are not able to account for individuals' heterogeneous behavioral processes (Greene and Hensher, 2010). To account for these issues, Williams (2006) proposed the generalized ordered probit model which allows a different parameter vector for each outcome. However, this extended model cannot ensure that the estimated probabilities are always positive; therefore, Greene and Hensher (2010) proposed a hierarchical ordered probit (HOPIT) model, which can address the negative probability issue. In this model, the exponential function of thresholds ensures that the thresholds are ordinally arranged[1]. This model also allows for systematic variations in the thresholds across decision-makers. The formulation of the thresholds can be written as (Greene and Hensher, 2010):

$$\mu_{i,j} = \mu_{i,j-1} + \exp(\theta_j + \gamma_j S_i) \tag{12}$$

where, θ_j is the intercept for each threshold j, S_i is the vector of variables affecting the thresholds for observation i, and γ_j is the vector of estimable parameters for S_i. In light of the above discussions, this study develops a zero-inflated hierarchical ordered probit with correlated error terms (ZIHOPC) model for estimating telecommuting participation and frequency.

[1] If the thresholds are not ordinally arranged (i.e. if a higher-numbered threshold is smaller than a lower-numbered one), that would result in subtracting a larger probability from a smaller one in Eqs. (7) and (10), yielding a negative probability of falling between the two thresholds.

Table 2
Estimation Results of zero-inflated hierarchical ordered probit model with correlated errors.

Variables	Parameter	t-Stat
Participation equation (Potential of Telecommuting Model):		
Constant	-0.98^{***}	−5.33
Gender: male	0.26^{***}	3.01
Income: low	-0.64^{***}	−5.64
Education: low	-0.67^{***}	−6.03
Trip distance: high	0.22^{*}	1.75
HH worker	0.18^{***}	3.04
Work flexibility	0.89^{***}	6.81
Occupation: transportation	-0.24^{*}	−1.65
Occupation: management	-0.61^{*}	−1.82
Occupation: health	-0.38^{***}	−3.30
Employment density: high	0.34^{***}	3.00
Population density	-0.07^{***}	−3.46
Activity equation (Level of Telecommuting Model):		
Constant	-0.62^{***}	−3.01
Income: med	0.49^{***}	6.03
Age: 35–55	0.20^{***}	3.31
Education: graduate	0.31^{***}	4.48
Trip duration	0.23^{***}	3.06
HH vehicle	0.14^{***}	4.15
Work flexibility	0.82^{***}	8.49
Occupation: government	-0.23^{**}	−2.19
Occupation: communication	0.31^{**}	2.27
Occupation: manufacturing	-0.16^{*}	−1.65
Employment density: low	-0.22^{***}	−3.10
Threshold variables:		
Work duration	0.03^{***}	2.89
Vehicle availability	-0.11^{*}	−1.72
HH vehicle: high	0.26^{***}	3.22
Threshold constants:		
θ_1	-1.60^{***}	−10.86
θ_2	-0.47^{***}	−4.08
θ_3	0.43^{***}	4.64
Correlation coefficient:		
ρ	0.28^{*}	1.91
log-likelihood at convergence	−3206.05	

Note: ***, **, * indicate significance at 1%, 5%, and 10% level.

4.2. Estimation results

The results of the proposed ZIHOPC model for estimating telecommuting participation and frequency are presented in Table 2. A full set of variables and variable interactions are tested, and the statistically significant variables at 90%, 95%, and 99% levels of confidence are presented in the table. A wide range of socio-demographic, land-use, and trip-related variables are found to be significant in individuals' telecommuting behavior.

The estimation results indicate that men are more inclined to telecommute. This is possibly because they have more access to telecommuting option and flexible jobs than women (Singh et al., 2013) who generally have lower negotiating power in the market (McCrate, 2005). Education and income level also significantly affect both telecommuting participation and the frequency level. The results show that workers with lower education and income are less likely to participate in telecommuting while those with graduate degree telecommute more frequently. This can be due to the fact that well-educated and high-income workers have higher ranks and bargaining power with their employers (Mannering and Mokhtarian, 1995; Peters et al., 2004).

Moreover, number of vehicles in the household is positively associated with telecommuting frequency. On a similar note, individuals who live in households with higher number of workers are more likely to participate in telecommuting. These trends can be interpreted as the effect of less responsibility of such individuals towards household errands (such as dropping off the kids at school) which can be handled by other members in such households (Singh et al., 2013). The results also suggest that workers who have access to vehicle for their work trips tend to telecommute less frequently, but this variable has no significant effect on telecommuting participation.

Moving to work-related variables, the results indicate that flexibility of work schedule increases the probability of both telecommuting participation and frequency, which is line with the findings of Sener and Bhat (2011). Occupation type also plays an important role in both participation and frequency level. We found that managers of companies or enterprises are less likely to participate in telecommuting, which can be because their critical roles at work enforce them to be present and directly interact with employees and clients. Furthermore, workers in health care or social assistance services are less likely to telecommute which is intuitive because of the necessity of face-to-face interactions with patients and other clients. Workers in manufacturing industries are also among the less frequent telecommuters because they are required to perform various types of physical activities at work, which is also mentioned in previous studies (e.g., Walls et al., 2007; Zhou et al., 2010). Table 2 indicates that workers in communication industry have more propensity to frequently telecommute whereas government employees are among the least frequent telecommuters.

The effect of trip-related and land-use variables on telecommuting participation and frequency level are also examined in this study. As expected, the results indicate that employees who live far away from their primary work location (i.e., more than 20 miles) are more likely to telecommute, which is in line with findings of previous studies such as Mokhtarian and Meenakshisundaram (2002). Similarly, travel time to the workplace has a positive effect on telecommuting frequency as it increases the probability of *almost every day* outcome and decreases the probability of *do not telecommute* outcome. Population density of home census tract and employment density of work census tract are also found to significantly affect both telecommuting participation and the frequency level. The results show that those who work in areas with a very high number of employees (i.e., more than 20,000 employees in the census tract) are more willing to participate in telecommuting. This can be because of the large corporations and companies located in Central Business District (CBD) areas, as they often provide the option of teleworking for employees to save space and reduce energy consumption. The results also suggest that individuals are less likely to telecommute *almost every day* (hence more likely *not to telecommute*) if they work in areas with a low number of employees (i.e., less than 3000 employees in the census tract).

5. Telecommuting implications

To conduct a reliable assessment of the potential impacts of telecommuting, results of the estimated participation and frequency model are implemented in the POLARIS activity-based framework. POLARIS is able to provide detailed activity-travel profiles and traffic condition in the network, which are the main source of input data for the MOVES emission model and Autonomie vehicle energy and GHG model. The following subsections elaborate on the integrated simulation settings, data flow among model components, and simulation results.

5.1. Simulation components and settings

POLARIS is an activity-based transportation systems simulation tool (Auld et al., 2016a) that integrates travel demand and transportation network flow into a unified modeling framework. The travel demand elements of the model, including activity generation, activity planning, and activity scheduling, are based on research into modeling activity planning and scheduling behaviors using a computational process model approach (Auld and Mohammadian, 2012). The demand model continuously integrates with traffic simulation where the generation, planning and scheduling of activities occurs in continuous time and is co-simulated along with the time-dependent traffic assignment and simulation. Further information about the interaction of components in the simulation framework can be found in Auld et al. (2016a).

To implement the estimated telecommuting adoption model, a new component is incorporated into the simulation framework, which determines whether the worker plans to telecommute in the simulation day. In this case, the worker's out-of-home work activity will be replaced by a flexible in-home work activity with the same duration[2]. The immediate result of this change is eliminating the home-to-work and work-to-home return trips. However, since the worker stays at home, his/her activity schedule is more flexible, which may provide incentive to conduct other activities during working hours. Furthermore, the activities that were previously planned to be performed in the home-work tour need to be re-planned in the simulation process. Therefore, a set of rule-based procedures are implemented to re-plan (whether he decides to cancel) or reschedule (whether he decides to shift) such activities.

By incorporating the telecommuting model in such an activity-based framework, we can account for multidimensional adaptation of individuals' travel behavior such as changes in activity generation decisions and departure time choices. Through an extensive post-processing procedure, the simulation results of POLARIS framework are converted to both individual vehicle drive cycles and link-level network information (including average speed, average travel time, and average traffic volumes of links). Afterwards, to evaluate how telecommuting affects the regional air quality and energy usage, we input the synthesized drive cycles to the Autonomie vehicle energy simulator and the calculated network measures to the MOVES emission simulator.

Autonomie is a widely used vehicle-energy simulator (Argonne, 2014) that focuses on vehicle powertrain and control simulation to predict energy consumption based on detailed vehicle speed drive cycles. Autonomie is capable of simulating a wide variety of powertrain components and configurations, including xEVs, fuel-cell vehicles and other advanced vehicle technologies, along with vehicle control logic, and is routinely used to forecast the impact of future vehicle technologies. POLARIS has been integrated to Autonomie in order to accurately represent energy consumption at a transportation system level (Auld et al., 2016b). A process has been developed that utilizes the average vehicle travel speed, stopped time, link entry speed and link exit speed generated by POLARIS to synthesize vehicle drive cycles for Autonomie. The process utilizes a Markov-Chain Monte-Carlo model developed using real-world drive cycles capture during GPS travel surveys (Karbowski et al., 2014). The process generates feasible drive-cycles that fit the constraints from the mesoscopic simulation. Autonomie then simulates vehicle operations over each drive cycle and outputs the fuel and/or electrical consumption for a given vehicle.

[2] It should be noted that we only consider the work-at-home option, due to lack of required information on other telecommuting options such as satellite offices.

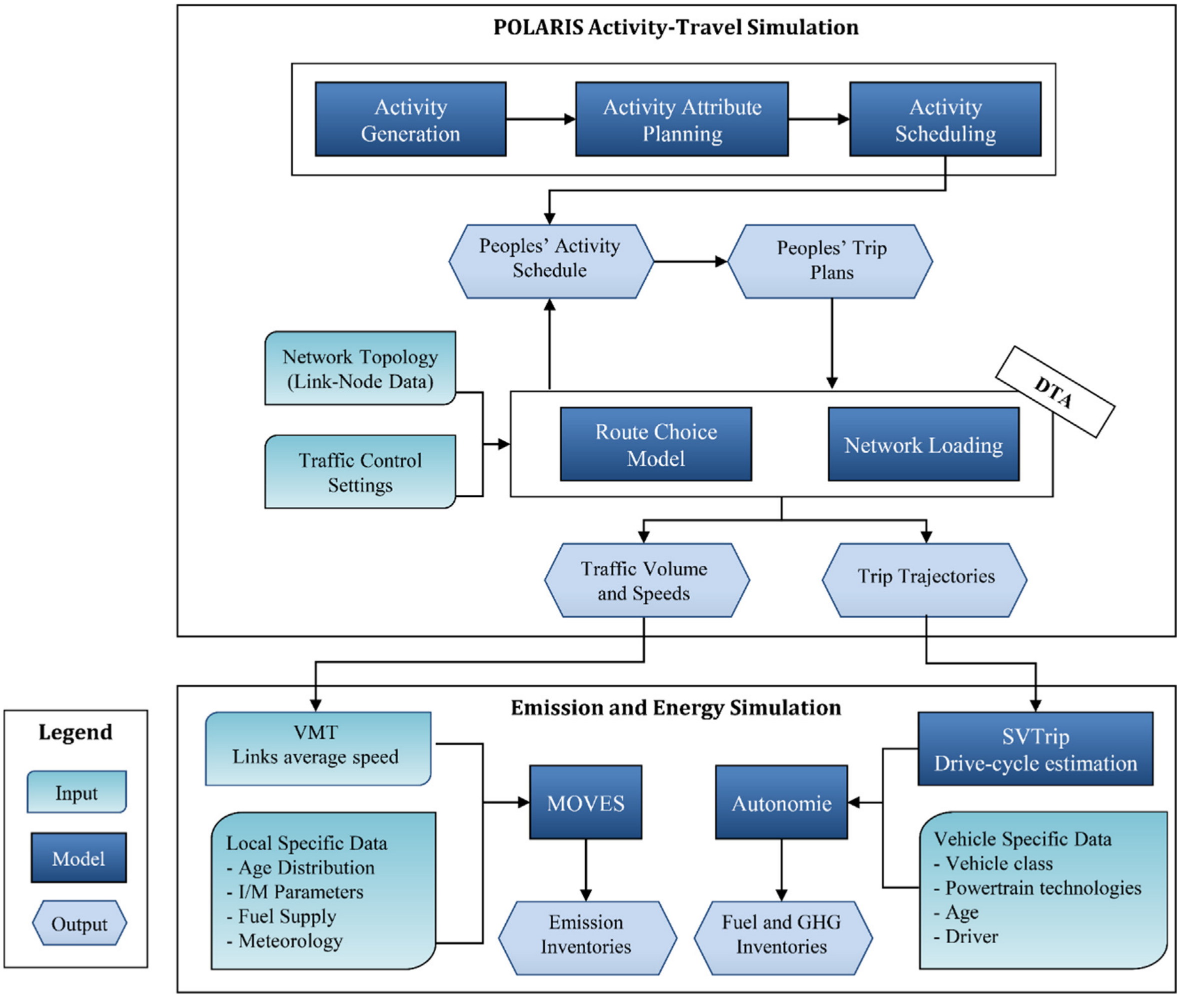


Fig. 3. Overview of integrated framework components.

MOVES (the US EPA's current emission model) is able to estimate mobile source emissions and fuel consumption of a wide range of vehicles types (USEPA, 2012). It can estimate both emission inventories and emission factors for different pollutants. In the county-level emission analysis, MOVES requires annual VMT for each defined vehicle type. Thus, the VMT obtained from the network simulator is extrapolated to the annual values. Then, monthly, daily, and hourly fractions are calculated using the VMT factor converters provided by EPA. Further, as for average speed distribution, the information on vehicles average speeds specific to vehicle type, road type, and the time of the day is provided by the POLARIS framework.

Considering each segment of the roadway as the unit of analysis, following Lee et al. (2015) and Tayarani et al. (2016), we create a lookup table tabulating emission rates for all combinations of time-of-day, road type, and average speed. Total emissions are then calculated by multiplying each roadway link's traffic volume by the emission factors that are matched based on the time-of-day, road type, and average speed. Finally, emission from all links are summed up to get the total emission inventories in the network for each hour and then for the whole day. In this study, Chicago metropolitan area (including 8 counties of Cook, DuPage, Grundy, Kane, Kendall, Lake, McHenry, and Will) and 3 counties of La Porte, Lake, and Porter in Northwest Indiana are selected as the geographic area of analysis. All links in the network are assumed as urban restricted access (urban highways that can only be accessed by an on-ramp) or urban unrestricted access (arterials, connectors, and local streets) in MOVES. In addition, MOVES default database associated with each considered county is employed to provide other input data including meteorology, I/M program, fuel supply, and vehicles age distribution. Fig. 3 represents the simplified modeling framework used to estimate the air quality and fuel consumption changes for the telecommuting scenarios.

5.2. Simulation results

To demonstrate the potential impacts of telecommuting, two scenarios are implemented in the simulation framework, in which the "work flexibility indicator" has been changed to represent a policy of offering increased flexibility of work schedule. As reported

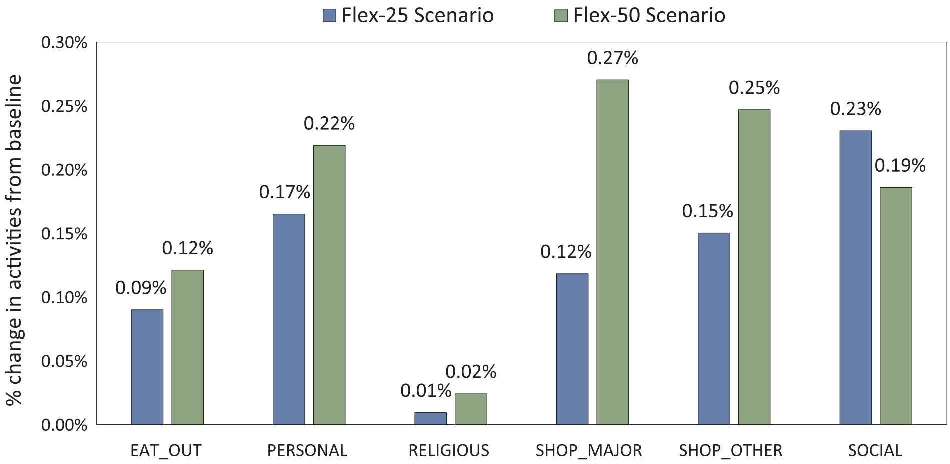


Fig. 4. Change in out-of-home discretionary activities for each scenario.

in the data description section (Table 1), about 12% of workers have flexible working time, which is considered as the base case (hereinafter, Flex–12) in this analysis. Two scenarios in which 25% and 50% of workers have flexible work schedule (named Flex–25 and Flex–50 scenarios) are also implemented in the simulation framework.

Analysis of simulation results revealed that increasing the work flexibility indicator leads to lower rates of out-of-home work activities and higher rates of in-home work activities. More specifically, we found that providing flexible work schedule for 25% and 50% of workers could respectively result in 1.06% and 3.04% reduction in the number of peak-period out-of-home work trips. This is an important finding providing evidence that work schedule flexibility can effectively alleviate peak-period work commutes. Fig. 4 demonstrates the occurrence of increasing discretionary activities, enabled by the increased work-at-home occurrences, with increases across all activity types except for social activities.

We also found that these changes in activity patterns decrease both vehicle miles traveled (VMT) and vehicle hours traveled (VHT) in the network. Indeed, network simulation results show that increasing the work flexibility index from 12% (base case) to 25% can lead to 0.22% and 1.0% reductions in total daily VMT and VHT, respectively. In addition, it is found that increasing the work flexibility index to 50% can reduce VMT and VHT by 0.69% and 2.09% compared to the base case. Fig. 5a–c illustrates the changes in daily traffic volumes across the study area, demonstrating the distribution of the changes in VMT and VHT geographically. The results show that as telecommuting increases, traffic volume is shifted out of the downtown and off of many of the main interstates leading into downtown and into many of the more suburban areas. In summary, our results endorse the fact that telecommuting policy has a substantial potential for decreasing network congestion, especially in dense CBD-type areas.

To evaluate the air quality benefits of telecommuting policy, we employ the proposed integrated framework to estimate GHG emissions and $PM_{2.5}$ inventories. We select GHG emission to study the effects of telecommuting on climate change and $PM_{2.5}$ to evaluate the health benefits of telecommuting, since $PM_{2.5}$ has been proven to have negative impacts on population health. We found that telecommuting has the potential to reduce GHG and $PM_{2.5}$ emissions by up to 0.7% and 1.14%, respectively (Table 3). The simulation results also indicate a similar reduction in fuel consumption in telecommuting scenarios. Fig. 5d shows how fuel consumption has been shifted throughout the region under the 50% flexibility scenario, with substantial fuel use savings in the CBD and near-CBD areas and along major highways, with increases in outlying suburbs and the south side of Chicago. In addition, Fig. 6 compares the change in hourly GHG emissions inventory in each scenario against the baseline, showing that most reductions in emission inventory occur during rush hours, with some increases even being observed after work hours.

We also use the simulation results to estimate the economic benefits of providing telecommuting in the Chicago metropolitan area. Assuming $36 in 2007 dollars per ton social cost of CO_2eq estimated by US EPA (Newbold et al., 2013), *Flex-25* and *Flex-50* telecommuting scenarios could annually save 3.9 and 9.1 million dollars, respectively. Adding the benefits from reduction in $PM_{2.5}$ emission and fuel consumption, assuming the benefits of 63,265 in 2007 dollars per ton cost of $PM_{2.5}$ (Heo et al., 2016) (converted to $2007 by Bureau of Labor Statistics) and $3/gallon fuel price (USEIA, 2017), the annual savings could reach up to 42 million dollars under the *Flex_50* telecommuting scenario.

6. Conclusion

This study presents the results of a comprehensive telecommuting analysis which aims to first, investigate workers' telecommuting adoption behavior and second, evaluate the consequences of this policy on travel behavior, network congestion, and air quality. The proposed framework consists of three distinct phases. In the first phase, a telecommuting adoption model is estimated to determine the factors associated with workers' propensity to adopt this policy and its frequency level. A zero-inflated hierarchical ordered probit model with correlated error terms is estimated to control for the excessive number of non-telecommuters in the dataset. In the second phase, the estimated model is implemented in the POLARIS activity-based framework to simulate the potential

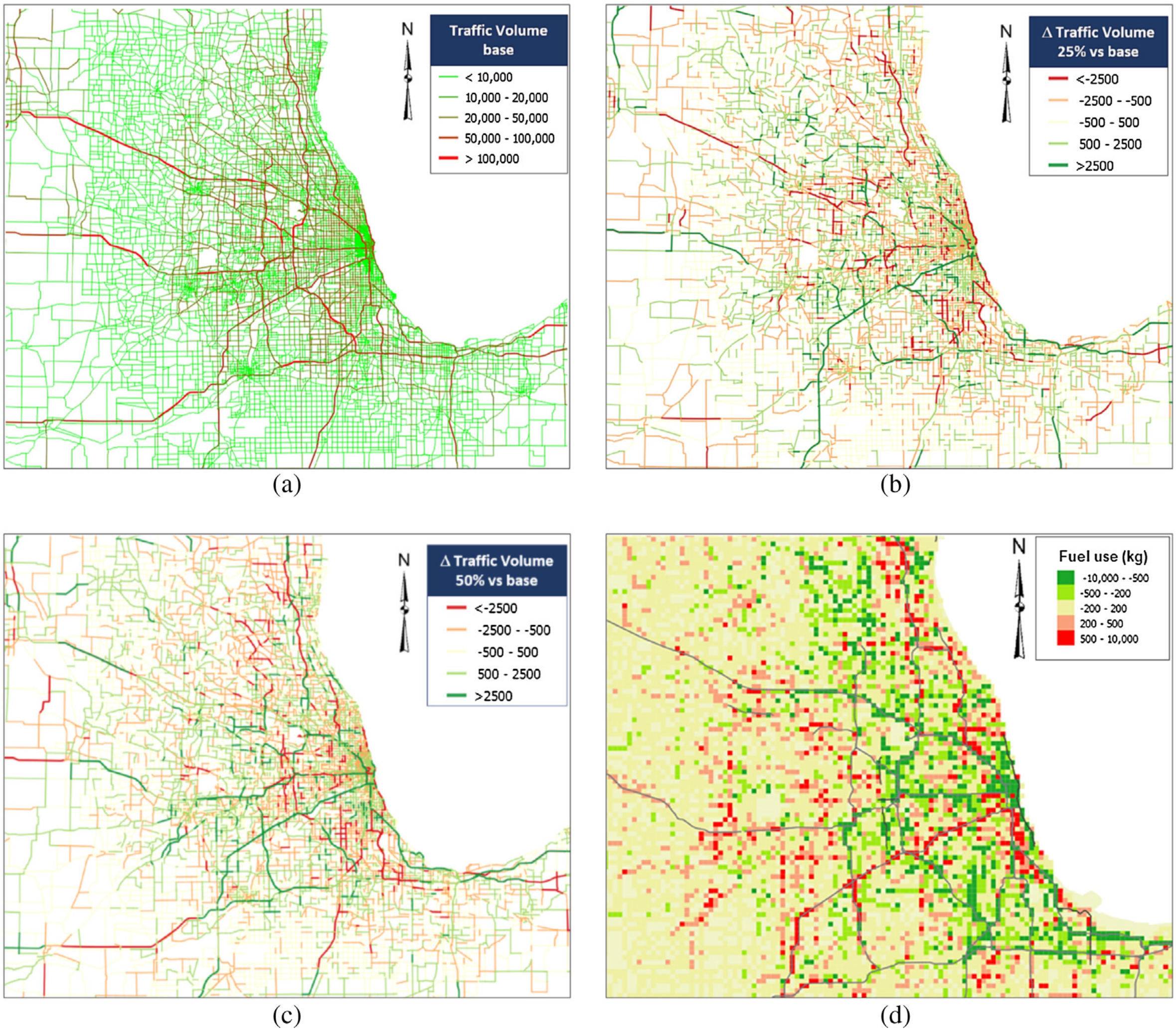


Fig. 5. (a) Baseline traffic volumes, changes in network traffic volumes: (b) Flex 25% vs. base, (c) Flex 50% vs. base, and (d) changes in fuel use per 1-km square grid: Flex 50% vs. baseline scenario.

Table 3
Changes in emissions and fuel consumption in telecommuting scenarios.

Emissions	Flex–12 (base case)	Flex–25 scenario	Flex–50 scenario
Average daily GHG (tone)	97630.6	97331.7 (−0.3%)[a]	96935.4 (−0.7%)
Average daily $PM_{2.5}$ (kg)	14630.9	14556.4 (−0.05%)	14464.2 (−1.1%)
Average daily fuel consumption (Million Gallons)	9.97	9.94 (−0.3%)	9.89 (−0.8%)

[a] Values in parentheses are percentage of change in Flex-25 and Flex-50 scenarios with reference to the base case.

effects of telecommuting on traffic congestion and network operation. Third, the Autonomie vehicle energy simulator and the MOVES emission simulator are used to estimate the potential changes in vehicular fuel use and emissions in the network as a result of this policy.

Two case scenarios are implemented in the simulation framework, in which the “work flexibility indicator” has been changed from 12% (base case) to 25% and 50% to represent a policy of offering increased telecommute flexibility. Analysis of the network simulation results indicates that telecommuting as a sustainable transportation policy can alleviate network congestion by reducing the total daily VMT and VHT up to 0.69% and 2.09%, respectively. We also found that this policy has the potential to reduce GHG and $PM_{2.5}$ emissions by up to 0.70% and 1.14%, respectively. The integrated platform presented in this study, not only can be used to

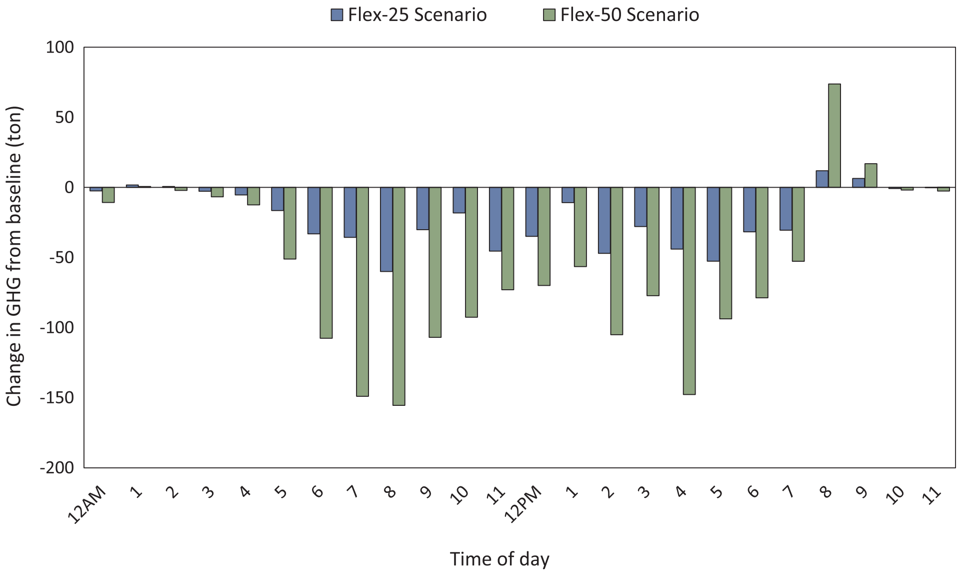


Fig. 6. Hourly inventory of GHG under telecommuting scenarios.

understand the true effects of telecommuting policy, but also offers a practical approach for testing potential effects of other TDM policies.

This research can be extended in several directions in future research. First, due to data limitations, we have focused only on home-based telecommuting; however, other forms of telecommuting should also be incorporated in future studies to obtain a more comprehensive assessment framework. In addition, employers' attributes which are expected to be influential in workers' telecommuting behavior have not been considered in this analysis (again, because of data limitations) and need to be incorporated in future studies.

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