Research Report – UCD-ITS-RR-13-44

# Three Essays on Energy Use & Transportation: (1) Dynamic Lifecycle Assessment of Advanced Bioenergy Pathways using GCAM Model; (2) Influence of Workplace Peers in the Commuting Decision in the U.S.; (3) Impact of Rapid Employment Growth on Traffic Congestion

December 2013

Geoffrey M. Morrison

Institute of Transportation Studies ◦ University of California, Davis
1605 Tilia Street ◦ Davis, California 95616
PHONE (530) 752-6548 ◦ FAX (530) 752-6572
www.its.ucdavis.edu

Three Essays on Transportation and Energy Use

By

GEOFFREY MICHAEL MORRISON

B.S. (Duke University) 2002
M.S. (University of California, Davis) 2011, 2012

DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Transportation, Technology, and Policy

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

Approved:

_____________________________________

Cynthia Lin, Chair

_____________________________________

Sonia Yeh

_____________________________________

Bryan Jenkins

Committee in Charge

2013

## TABLE OF CONTENTS

## ACKNOWLEDGEMENTS

I received tremendous support in carrying out my dissertation and can hardly claim it as my own. First, I would like to thank my parents who tirelessly support me no matter where (geographically or topically) my interests take me. There is never a way I could repay them.

I am also deeply indebted to my two main academic advisors, C.-Y Cynthia Lin and Sonia Yeh. Both poured hundreds of hours of teaching, advising, and revising into me and my work the past five years. They are amazing role models and top notch academics whose influence I will undoubtedly feel the rest of my career. I also thank my other committee members including Bryan Jenkins, Joan Ogden, and Alissa Kendall for helping review my methodology and overall approach in my dissertation.

Lastly, I would like the thank the US Department of Transportation for generous funding through the Eisenhower Graduate Fellowship program and the University of California, Davis STEPS (Sustainable Transportation Energy Pathways) program for additional generous funding.

# Three Essays on Transportation and Energy Use


## Abstract

My dissertation examines three questions related to transportation and energy use. In the first essay, I investigate the influence of workplace peers on an individual's travel decisions to work. Using a large dataset of U.S. military commuters and instruments to address the endogeneity of the decisions of one's workplace peers, I show that workplace peers positively influence one another's drive/no-drive decision and carpool/drive-alone decision. I also explore whether conventional measures of social status and seniority (i.e. income, education, age, and number of years in the military) predict who exerts the strongest influence on others, and find that intragroup influence appears to be stronger and more consistent than intergroup influence, which suggests that for commute decisions, social validation is a stronger motivator towards conformity than authority.

In the second essay, I examine the short-run impacts of rapid increases in regional employment on travel time to work by exploiting exogenous variation resulting from movements of military troops during the 2005 Base Realignment and Closure (BRAC) process. Employment levels often change more quickly than other factors that influence regional travel demand (e.g. number of two-worker households, vehicle ownership rates, travel preferences, etc.), making effective anti-congestion measures difficult to plan and implement. The BRAC process provides a convenient quasi-experimental framework to measure the short-run, congestion-related effects of employment growth on travel times because it occurred exogenous to the normal transportation planning process. I use difference-in-difference, difference-in-difference-in-difference, and instrumental variable methods to estimate these effects. The results are quite

robust -- each additional commuter added to the transportation network per square kilometer adds 0.0032-0.055 additional minutes of travel for all other individual commuters in the short run. According to back-of-the-envelope calculations, the short-run economic travel time cost of the 2005 BRAC is estimated to have cost communities near BRAC-affected bases between $155 million and $1.5 billion per year. This paper has relevance for both transportation planners who seek effective growth strategies and Department of Defense officials who seek to mitigate transportation impacts from troop movements and base closures.

In the third and final essay, I examine how the carbon intensity (grams CO2e/MJ) of important upstream stages of bioenergy production will change over the next century for three generic energy pathways (biogas, bioliquids, bioelectricity) and five feedstocks (miscanthus, switchgrass, jatropha, eucalyptus, and willow). I construct an updated version of the Global Change Assessment Model (*GCAM*) which accounts for regional, temporal, and feedstock heterogeneity in five upstream stages: fertilizer production, fertilizer application, harvest energy, biomass transport energy, and pre-processing energy. Overall, I find that the median carbon intensity of these five upstream stages across scenarios declines by about 50% between 2020 and 2095 for bioelectricity, while bioliquids and biogas remain relatively flat. These trends result from several shifts in global agriculture production and land use. The shifting cultivation of biocrops between agricultural regions increases $N_2O$ emission intensity until the year 2050 and decreases it thereafter. Similarly, carbon intensities of bioenergy will decrease due to improved yields but this effect will be dampened before 2050 and accelerated after 2050 as effective yield of bioenergy moves towards less productive and more productive land, respectively. As yields increase, the supply radii of bioenergy agrosystems decreases by an average of 21% across scenarios between 2020 and 2095 assuming an average input of 2.0 million tons of biomass per yr$^{-}$. My results suggest that shifts in land use play as important role in determining the trajectory of upstream greenhouse gas intensity of bioenergy in the future.

**ESSAY ONE**

Driving in Force:

The Influence of Workplace Peers on Commuting Decisions on U.S. Military Bases

## 1.1 INTRODUCTION

Workplace peers have been shown to play an important role in daily decision-making within the workplace (Salancik and Pfeffer, 1978). Past research also demonstrates that peer influences – mainly from an intra-household perspective – can affect travel-related decisions like telecommuting (Paez and Scott, 2008; Wilton et al., 2011), bike commuting (Heinen et al., 2011), and walking to school (McDonald, 2009). However, no empirical research links mode choice decisions of an individual's workplace colleagues to his/her own travel choices. This paper uses a large dataset from the U.S. Census to examine whether an individual's decision to drive or carpool to work is influenced by the drive or carpool decisions of his or her workplace peers.

There are three sources of endogeneity that must be overcome when estimating peer effects. The first is the simultaneity problem of reflection: an individual exerts influence on the group just as the group influences the individual (Manski, 1993). The second is an omitted variables problem which exists because of the impossibility of controlling for all travel-related variables that affect both an individual and his/her workplace colleagues.[1] Lastly, there is a group self-selection problem because individuals may choose careers based on similar attitudes.

[1] Examples of unobservables that are difficult to quantify but could affect both an individual and his/her workplace

This paper addresses these endogeneity problems using instrumental variables based on aggregated group demographic characteristics, which are shown to be unrelated to an individual's mode choice decision but are related to the workplace peers' preference for a given mode (Brock and Durlauf, 2001; Brock and Durlauf, 2002; Walker et al., 2011). I verify the appropriateness of the instruments with post-regression tests. I also control for important predictors of travel behavior, including individual-level variables such as income, age, education level, immigration status, number of dependents, gender, household vehicle ownership; and region-level land-use and transit availability variables such as employment density and transit availability.  For robustness, I run a variety of model specifications.

Social psychologists often use three interrelated components – cognition (information), affect (feelings), and conation (behavioral intentions) – to describe the main drivers of human behavior. Because of the important role the workplace plays in our daily lives -- American adults spend 22% of all hours at the workplace[2] -- it is possible the workplace affects each of these components. For example, an individual may acquire knowledge about carpool lanes, transit incentives, bike routes, etc. during an informal "water-cooler" talk, thus expanding that individual's awareness about the benefits and costs of choosing a given mode (cognition). Moreover, as shown by Dumas and Dobson (1979), if the normative behavior of a peer group is one particular travel mode, then an individual's affect will be influenced in favor of that mode. Norm transmission intensifies when the norms are communicated by individuals of higher social status (authority) and by members of one's own social group (social validation) (Cialdini and Trost, 1998). Lastly, conation refers to an individual's behavioral intentions which could be influenced by either formal or informal workplace goals related to commute behavior.

[2] The average worker in the U.S. between the years 2000-2009 worked for 40.5 hours per week and 47.2 weeks per year (Ruggles et al., 2009)

A well-known weakness of econometric analyses of travel behavior is that they often rely on cross-sectional datasets – like the National Household Travel Survey or local travel surveys – and thus fail to exploit variation in behavior over time. Similarly, travel datasets that include a time dimension are typically aggregated to the county-, city-, state-, or nation-level and thus neglect important variation between individuals. The dataset used here – the American Community Survey (ACS) – is a repeated cross-section data set that includes variation across both individuals[3] and time, and is suitable to my needs because of its focus on the commute to work.

I focus in particular on military personnel and their workplace peers working on the same military base because, unlike many workplaces, the military work environment is limited to a specific geographic and social space: that within the base perimeter. Thus, the physical movements of military personnel and the people with whom they interact are arguably better controlled than many other work environments. Additionally, to examine workplace peer influence requires a sizeable sample from a given workplace. I am not aware of other surveys with commute to work variables in which such a large number of individuals (831,195 total) can be identified and located at a specific worksite.

I recognize that a sample of military commuters may differ in travel choices from a set of randomly chosen civilian workers. To better understand these differences, I compare military and civilian commuters across important travel-related variables and use a series of regressions to show that military individuals have a slightly higher preference for driving than civilian counterparts.

[3] As discussed below, important socio-economic and demographic variables are at the individual-level. However, the built environment, transit, and group demographic instrumental variables are aggregated to the PUMA-level.

My results show that military personnel are influenced by their peers in both the drive/no-drive decision and the carpool/drive-alone decision. Among all military commuters, individuals with more years in the military service, lower education, and fewer hours worked per week are most highly influenced by peers in the drive/no-drive decision. For the carpool/drive-alone decision, the peer influence is strongest among older individuals with high education, who work fewer hours per week, and who live in urban areas.

I also explore whether conventional measures of social status and seniority (i.e. income, education, age, number of years in the military) predict who exerts the strongest influence on others, and find instead that intragroup influence (e.g. young workers' influence on other young workers) appears to be stronger and more consistent than intergroup influence (e.g. older workers' influence on younger workers), which suggests that social validation is a stronger motivator towards conformity than authority.

This research is the first to demonstrate that travel decisions made by one's workplace colleagues predict his/her mode choice to work and suggests that workplace interventions that incentivize carpooling and non-auto modes will have a positive feedback on desired mode shifts.

This paper is organized as follows: Section 2 discusses the datasets, variable creation, and modeling approach used to examine workplace peer effects on travel. Section 3 investigates differences between a military commuter and a civilian commuter. Section 4 presents the main results on peer effects. Finally, in Section 5 I present a discussion and conclusion.

## 1.2 DATA

My main dataset – the ACS – is available for download from the IPUMS-USA website maintained by the University of Minnesota Population Center (Ruggles et al., 2010). Each year, approximately 3 million individuals are surveyed for the ACS, which means approximately 10% of the U.S. population is sampled in each 10-year cycle. I use the years 2000, 2006, 2007, 2008, and 2009. The years 2001-2004 were not included because they do not include a full set of variables. The U.S. Census Bureau uses a multistage sampling design to ensure a representative sample each year which includes stratification, clustering, and weighting of individuals.[4] PUMAs are the smallest identifiable geographic region in census data at the person-level and typically have ~100,000 people. However, by identifying military personnel within the PUMAs and assigning those personnel to a unique military base I am able to dramatically reduce the size of the geographic region even further.[5]

Each individual in the dataset appears a single time and reports a single commute mode choice decision. The binary decision to drive to work versus taking other modes (bus, rail, walk, cycle, ferry, taxi, worked at home, other) is made by 88% of full-time civilian workers and 96% of military members. The decision to carpool is a subset of the individuals who respond they drive to work; among full-time workers and military members, 12% and 11% of individuals carpool versus drive alone, respectively.[6]

In addition to individual-level control variables – such as age, income, education, family status, vehicles in household, and immigration status – I create region-level land-use and transit availability variables (henceforth referred to as "built environment" variables) which have been shown to affect travel (Bento et al., 2005). The built environment variables include employment

[4] As recommended by Ruggles et al. (2010), to help correct for the homogeneity of individuals in the same household and geographic region, our models use a Taylor Series Linearization (TSL) procedure in which an individual's household is the primary sampling unit and an individual's residential geographic area (called a "PUMA" – a public use microdata area) is the stratum.
[5] Active duty military, veterans, and civilians are identified with the census variable "vetstat" which defines individuals as active, veteran, or civilian.
[6] If respondents took more than one mode to work (e.g. car, rail), the survey instructs them to mark the mode in which they travelled the greatest distance.

density, bus density, train/subway density, and dummy variables for whether an individual lives in an urban, rural, or suburban environment.[7]

The use of built environment density variables is common in the travel literature (see e.g., Cervero and Kockelman, 1997; Zhang, 2004; Heres-Del-Valle and Neimeier, 2011). While these variables sometimes fail to capture complex transportation systems, some authors argue they act as reasonable proxies for important land use variables in travel decisions (Steiner, 1994; Dunphy and Fisher, 1996) [8,9]. Each density variable is created using occupational codes in the ACS. For example, "bus density" is the number of full-time bus operators within each PUMA divided by the area (in square-km) of the PUMA. The census provides each respondent's home and work PUMA which allows us to create separate built environment variables for both locations (i.e. workplace bus density and home bus density).

Built environment variables are often highly correlated. However, my large sample size provides considerable variability across different built environments, and the coefficients I estimate on most of these variables are significant, which suggests that they all belong in the model and omitting some of them would cause the estimates to be biased.

I control for the log average gasoline price by year and state (DOE, 2010) to help control for differences in driving expenses, and I include state-level fixed effects to control for structural differences between states in travel behavior. Lastly, the military-only peer effects models in Section 4 also include base fixed effects.

[7] The urban, rural, and suburban are pre-defined by the U.S. Census and are mapped as follows: urban = "central city," rural = "not in metro area"; suburbia = "outside central city."

[8] These variables are created at the PUMA-level using worker identification codes in the ACS. For example, bus density is the density of bus drivers who work in a given PUMA in a given year.

[9] Other measures, such as the "3 D's" (density, diversity, and design) put forth by Cervero and Kockleman (1997), use a combination of densities and indices to measure the built environment.

## 1.3 MILITARY VERSUS CIVILIAN COMMUTERS

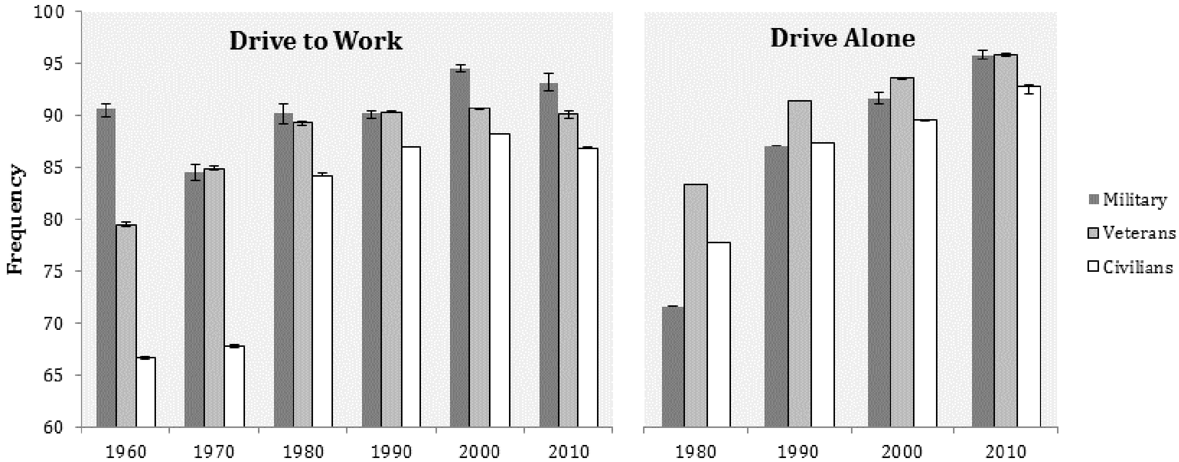
How do characteristics of military commuters and their commuting environment differ from those of civilian American commuters? I answer this question by first comparing distributions of each control variable for three commuter groups in the U.S.: military, veterans, and civilians. The veteran group is an interesting addition because they are still linked to the military (via their prior career) but no longer commute to a military base and therefore should not be affected by the military base's built environment variables.[10] I then estimate a discrete response model which predicts the probability of driving or carpooling using data for the general population, and use dummy variables for military, civilian, and veteran to examine whether being in the military has an effect of the probability of driving or carpooling after controlling for socio-economic, demographic, and built environment variables.

Figure 1 plots the percentage of military, veterans, and civilians who drive to work and the percentage of drivers who drive alone to work for every 10 years between 1960 and 2010.[11] Military personnel have a slightly greater preference for driving to work than their civilian counterparts, and higher or the same preference as veterans (Ruggles et al., 2010). Among the group choosing to carpool or drive alone, the military were less likely to drive alone than both veterans and civilians in 1980 but drove alone more than the civilians and at the same rate as veterans in 2010.

[10] However, it is likely that some self-selection still occurs since veterans often still live in cities with military bases (Ruggles et al., 2010)

[11] Models in Section III use all three groups while the models in Section IV use only the active duty military subgroup. All samples omit military personnel who live in barracks, on ships, or in military prisons, focusing instead on military members who live offbase in private houses or apartments and commute daily to base. According to data from the U.S. Census Bureau (Ruggles et al., 2010) the omitted group, 35% of whom drive to work, comprises 23% of all military personnel.

**FIGURE 1.1: Percentage of military, veterans, and civilians who drive to work (versus take other modes) and the percentage of drivers who drive alone to work (versus carpooled), 1960-2010, with 95% Confidence Intervals**




*Data source:* Ruggles et al., 2010

*1.3.1 Individual-Level Variables*

Military and civilian workers differ across a number of important individual characteristics, many of which also influence driving and carpooling decisions. Table 1 gives summary statistics for individual-level variables for both military and civilian workers including socio-economic, immigration-related, family-related variables.[12]

Two-sample t-tests reveal significant differences in the means of individual-level variables of military workers versus civilian workers for all variables. The military drives at a higher frequency and, among those who choose to drive, the military carpools at a lower frequency than civilian counterparts.

[12] The civilian group includes all non-military, full-time workers in the U.S. between the ages of 17 and 61 (to correspond with military age requirements) and who report a mode to work.

In a paper using similar discrete response models as used here, Bento et al. (2005) showed that the individual-level variables that most positively influenced the drive decision in the U.S. among commuters in the 2001 Nationwide Personal Travel Survey (NPTS) included age and income, while the individual-level variables that most negatively influenced driving included the number of children. As seen in Table 1, military commuters have some characteristics that I would expect to increase the probability of driving to work compared to civilian commuters, such as a lower mean income and fewer children on average. They also have some characteristics that I would expect to decrease the probability of driving to work compared to civilian commuters, such as a lower mean age. In sum, from this set of predictor variables, it is difficult to say whether the military sub-group of commuters is inherently more or less likely to drive than their civilian counterparts.

Past research examining the individual-level predictors of carpooling suggests that age and vehicles per adult household member are negatively related to the decision to carpool (Belz and Lee, 2012). Table 1 demonstrates that, for these variables, military members have lower mean age and slightly fewer vehicles per household member than civilian commuters, and thus have some characteristics that make them less likely to carpool.

The census dataset prohibits us from also considering attitudinal factors in my discrete response models. In particular, it is possible that military members have a predisposition towards a given mode prior to entering the military service. I discuss this potential self-selection bias at the end of this section.

*1.3.2 Built Environment Variables*

Table 2 gives a similar comparison of household-level and PUMA-level built environment variables. As seen in this table, military workers tend to live and work in places with locations with lower worker and transit densities than civilians (approximately three times as low).[13] Past research suggests a negative relationship between residential and employment density and the decision to drive and the decision to carpool, and that characteristics of the work built environment have a larger impact on the decision than the residential built environment (Chatman, 2003; Bento et al., 2005; Belz and Lee, 2012).

Some of the low density of military residence and workplace can be attributed to geographic development patterns. Most bases have an area of dense employment with administrative buildings and operations offices; training areas for physical fitness or combat exercises; a commercial area with retail shops and restaurants; a warehouse district for the storage of machinery, tools, and vehicles; and residential communities in the form of barracks, ships' berthings, and base housing. Also, military bases are often separated from housing or urban centers by a "buffer zone" which is often characterized by low to medium density retail (e.g. strip malls). Military personnel entering a base must pass through security gates which can act as bottlenecks for the morning commute and might discourage non-auto modes.

Tables A2 and A3 in the Appendix compare the individual-level and built environment variables, respectively, for veterans and civilian workers.

[13] Despite the relatively low density of military workplaces and residences, the percentage of workers who report living in an urban versus rural environment is similar between civilians and military workers. One explanation for this apparent discrepancy is that military bases are often located near medium (less than 1 million people) to small (less than 100,000) sized cities where densities are lower, on average, than larger cities.

**TABLE 1.1: Two Sample t-Tests of Military and Civilian Worker Populations (2000, 2006-2009 ACS)**

| Sample size (weighted) | Civilian Workers n = 9,860,327 (591,899,750) | | | | Military Workers n = 23,118 (1,256,953 ) | | | | Sig |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | |
| **Commute** | | | | | | | | | |
| Drive to work (dummy) [alternatives are bus, train, ferry, taxi, walk, cycle, work at home, other] | 0.88 | 0.33 | 0 | 1 | 0.96 | 0.18 | 0 | 1 | *** |
| Carpool (dummy) [alternative is to drive alone] | 0.12 | 0.33 | 0 | 1 | 0.11 | 0.31 | 0 | 1 | *** |
| **Socio-economic / Demographic** | | | | | | | | | |
| Age (years) | 39.39 | 12.19 | 17 | 61 | 30.91 | 8.1 | 17 | 61 | *** |
| Education level (years) | 13.5 | 2.54 | 4 | 21 | 13.74 | 1.9 | 4 | 21 | *** |
| **Family** | | | | | | | | | |
| Family income ($10,000) | 6.65 | 6.06 | -3.1 | 137 | 5.17 | 3.4 | 0.06 | 48.9 | *** |
| Hours worked per week (hours) | 39.9 | 11.89 | 1 | 99 | 51.3 | 13.76 | 0 | 99 | *** |
| Female employed worker (dummy) | 0.47 | 0.50 | 0 | 1 | 0.16 | 0.37 | 0 | 1 | *** |
| Family size (number) | 2.69 | 1.49 | 1 | 31 | 2.5 | 1.44 | 1 | 12 | *** |
| Vehicles per adult in household (number) | 1.25 | 0.69 | 0.05 | 6 | 1.21 | 0.66 | 0.09 | 6 | *** |
| Number of children (number) | 0.56 | 0.93 | 0 | 9 | 0.47 | 0.89 | 0 | 8 | *** |
| **Immigration** | | | | | | | | | |
| Immigrated to US 0-5 years ago (dummy) | 0.02 | 0.13 | 0 | 1 | 0.01 | 0.07 | 0 | 1 | *** |
| Immigrated to US 5-10 years ago (dummy) | 0.02 | 0.15 | 0 | 1 | 0.01 | 0.11 | 0 | 1 | *** |
| Immigrated to US >10 years ago (dummy) | 0.08 | 0.3 | 0 | 1 | 0.06 | 0.26 | 0 | 1 | *** |

Notes: For each variable, a two-sample t-test was conducted to compare the military population with the non-military population. The “Sig” column reports the significance levels from the test. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

**TABLE 1.2: Two Sample t-Tests For Military and Civilian Built Environments (2000, 2006-2009 ACS)**

| | Civilian Workers n = 9,860,327 (591,899,750) | | | | Military Workers n = 23,118 (1,256,953 ) | | | | Sig |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | |
| **Residential PUMA** | | | | | | | | | |
| Employment density (workers/sq. km) | 1,755 | 6399 | 0.2 | 156,495 | 747.7 | 1598 | 1.56 | 29,374 | *** |
| Bus density (bus workers/sq. km) | 7.10 | 19.81 | 0 | 317 | 2.55 | 7.03 | 0.004 | 169 | *** |
| Train density (train workers/sq. km) | 0.29 | 1.56 | 0 | 25 | 0.08 | 0.7 | 0 | 18 | *** |
| Lives in city center (dummy) | 0.15 | 0.36 | 0 | 1 | 0.16 | 0.33 | 0 | 1 | *** |
| Lives in rural area (dummy) | 0.16 | 0.34 | 0 | 1 | 0.13 | 0.4 | 0 | 1 | *** |
| Lives in suburban area (dummy) | 0.35 | 0.44 | 0 | 1 | 0.26 | 0.48 | 0 | 1 | *** |
| Lives in metropolitan area, land use type not specified (dummy) | 0.34 | 0.47 | 0 | 1 | 0.45 | 0.5 | 0 | 1 | *** |
| **Workplace PUMA** | | | | | | | | | |
| Employment density (workers/sq. km) | 3,360 | 15,135 | 0.2 | 156,495 | 1017.3 | 2437.3 | 1.16 | 17,606 | *** |
| Bus density (bus workers/sq. km) | 10.40 | 33.67 | 0 | 317 | 3.40 | 9.12 | 0.005 | 169 | *** |
| Train density (train workers/sq. km) | 0.52 | 2.67 | 0 | 25 | 0.14 | 0.863 | 0 | 18 | *** |

Notes: For each variable, a two-sample t-test was conducted to compare the military population with the non-military population. The “Sig” column reports the significance levels from the test. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

*1.3.3 General Population Models*

To assess whether the military and civilians differ in their propensity for driving and carpooling I estimate a discrete response model by regressing the probability of driving (or carpooling) on a number of control variables, $x_{it}$, which have been shown to predict commute decisions (Bento et al., 2005). I estimate both a linear probability model:

$$\Pr(I_i = 1) = x_{it}'\beta_1 \tag{1}$$

and a probit model:

$$\Pr(I_i = 1) = \Phi(x_{it}'\beta_1) \tag{2}$$

where $\Pr(\cdot)$ denotes probability, $I_i$ is an indicator for individual *i* choosing to drive (or carpool), $\Phi(\cdot)$ denotes the standard normal cumulative distribution function, and $\beta_1$ is a vector of parameters of the same length as $x_{it}$. $I_i$ is the decision to drive (drive models) and carpool (carpool models) to work. The alternative to driving to work is walking, biking, or taking public transit. The alternative to carpooling is driving alone. These models are estimated using the same military and civilian individuals used in Tables 1 and 2 and include dummy variables for being in the military and being a recent or not a recent veteran. Significant coefficients for the dummy variables suggest that factors beyond common predictors of travel contribute to differences in travel choices between the military/veteran individuals and the general population.

Table 3a gives results of the linear probability and probit models for the drive/no drive decision. Table 3b gives the same results for the carpool/drive alone decision. In both sets of models, the military and veteran dummy variables are almost all significant and are among the highest magnitude coefficients. Focusing on the linear probability model results, being in the military increases the probability of driving by between 0.009 to 0.049 and decreases the probability of carpooling by 0.01 to 0.03. Being a veteran increases the probability of driving by between 0.012 to 0.025 and being a veteran separated from the military for over 2 years decreases the probability of carpooling by 0.02.

Table 4 is a robustness check for the military dummy variables using two other model specifications of the linear probability model. In the first robustness test, I change the income control from the natural log of income to the real-valued function (in units of $10,000). This change allows for the inclusion of an additional 663,481 observations in the drive/no-drive model and 522,207 observations in the carpool/drive alone model.

In the second robustness test, I only consider heads of households instead of all working household members. This helps control for inherent homogeneity between household members and is used by Marion and Horner (2007) who examine behavior of "extreme commuters"[14] with U.S. census data.

In all the specifications, the coefficients on all the dummy military and veteran variables except some in the household head model of the drive decision (Model 6) are all positive and significant at the 5% level for the drive/no-drive decision and negative and significant for the carpool/drive alone decision.

[14] Extreme commuters are those whose one-way commute is greater than 90 minutes (Marion and Horner, 2007).

## TABLE 1.3a: General Population Models of Drive/No Drive Decision

| | Linear Probability Model (Model 1) | | Probit Model (Model 2) | |
|---|---|---|---|---|
| | Coeff. | Std. Err. | Coeff. | Std. Err. |
| **Military-related** | | | | |
| Military member in year 2000 (dummy) | 0.009*** | (0.00) | 0.221*** | (0.01) |
| Military member in year 2006 (dummy) | 0.016*** | (0.00) | 0.294*** | (0.01) |
| Military member in year 2007 (dummy) | 0.003*** | (0.00) | 0.106*** | (0.01) |
| Military member in year 2008 (dummy) | 0.049*** | (0.00) | 0.525*** | (0.01) |
| Military member in year 2009 (dummy) | 0.043*** | (0.00) | 0.410*** | (0.00) |
| Veteran (separated >2 yrs ago) (dummy) | 0.025*** | (0.00) | 0.200*** | (0.00) |
| Veteran (separated <2 yrs ago) (dummy) | 0.012*** | (0.00) | 0.0829*** | (0.00) |
| **Socio-economic / Demographic** | | | | |
| Age (yrs) | 0.001*** | (0.00) | 0.0064*** | (0.00) |
| Age-squared (yrs^2) | -2.06*** | (0.00) | -1.3e-4*** | (0.00) |
| Education (10s of years in school) | -0.03*** | (0.00) | -0.20*** | (0.00) |
| **Family** | | | | |
| Family Income ($10,000) | 0.017*** | (0.00) | 0.101*** | (0.00) |
| Hours worked per week (100 hours) | 0.072*** | (0.00) | 0.41*** | (0.00) |
| Female employed worker (dummy) | 0.003*** | (0.00) | 0.0245*** | (0.00) |
| Family size (100s of people) | -0.11*** | (0.00) | -0.45*** | (0.00) |
| Vehicles per adult in household (number) | 0.018*** | (0.00) | 0.119*** | (0.00) |
| Number of children (100s) | 0.33*** | (0.00) | 1.80*** | (0.00) |
| **Immigration** | | | | |
| Immigrated to U.S. 0-5 years ago (dummy) | -0.06*** | (0.00) | -0.329*** | (0.00) |
| Immigrated to U.S. 5-10 years ago (dummy) | -0.02*** | (0.00) | -0.129*** | (0.00) |
| Immigrated to U.S. >10 years ago (dummy) | 0.001*** | (0.00) | -0.000249 | (0.00) |
| **Household Built Environment** | | | | |
| Workers density (million workers/sq. km) | 0.10*** | (0.00) | -1.43*** | (0.00) |
| Bus density (1,000 bus workers/sq. km) | -1.04*** | (0.00) | -3.23*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 3.01*** | (0.00) | 14.60*** | (0.00) |
| Lives in city center (dummy) | -0.01*** | (0.00) | -0.105*** | (0.00) |
| Lives in rural area (dummy) | -0.00*** | (0.00) | -0.0359*** | (0.00) |
| Lives in suburban area (dummy) | 0.007*** | (0.00) | 0.0290*** | (0.00) |
| **Workplace Built Environment** | | | | |
| Worker density (million workers/sq. km) | -0.90*** | (0.00) | 3.20*** | (0.00) |
| Bus density (1,000 bus drivers/sq. km) | -2.30*** | (0.00) | -10.70*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 3.33*** | (0.00) | 30.60*** | (0.00) |
| **State-Level** | | | | |
| Log of avg. yearly gas price in state ($2009) | -0.007*** | (0.00) | -0.188*** | (0.00) |
| **State and year fixed effects** | Yes | | Yes | |

| | | |
|---|---|---|
| p-value (Pr > F) | 0.0000**** | 0.0000**** |
| Observations | 491,674,903 | 9,211,459 |

Notes: Standard errors in parentheses. For the probit model, marginal effects are reported. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

### TABLE 1.3b: General Population Models of Carpool/Drive Alone Decision

| | Linear Probability Model (Model 3) | | Probit Model (Model 4) | |
|---|---|---|---|---|
| | Coeff. | Std. Err. | Coeff. | Std. Err. |
| **Military** | | | | |
| Military member in year 2000 (dummy) | -0.02*** | (0.00) | -0.114*** | (0.01) |
| Military member in year 2006 (dummy) | -0.01*** | (0.00) | -0.0541*** | (0.01) |
| Military member in year 2007 (dummy) | -0.03*** | (0.00) | -0.214*** | (0.01) |
| Military member in year 2008 (dummy) | -0.02*** | (0.00) | -0.105*** | (0.00) |
| Military member in year 2009 (dummy) | -0.02*** | (0.00) | -0.0997*** | (0.00) |
| Veteran (separated >2 yrs ago) (dummy) | -0.02*** | (0.00) | -0.150*** | (0.00) |
| Veteran (separated <2 yrs ago) (dummy) | -0.003 | (0.00) | -0.00879*** | (0.00) |
| **Socio-economic / Demographic** | | | | |
| Age (yrs) | -0.002*** | (0.00) | -0.0103*** | (0.00) |
| Age-squared (yrs^2) | 2.1e-5*** | (0.00) | 7.2e-5*** | (0.00) |
| Eduction (10s of years in school) | -0.10*** | (0.00) | -0.45*** | (0.00) |
| **Family** | | | | |
| Family Income ($10,000) | -0.01*** | (0.00) | -0.0915*** | (0.00) |
| Hours worked per week (100 hours) | 0.02*** | (0.00) | 0.06*** | (0.00) |
| Female employed worker (dummy) | -0.003*** | (0.00) | -0.0176*** | (0.00) |
| Family size (100s of people) | 1.60*** | (0.00) | 6.57*** | (0.00) |
| Vehicles per adult in household (number) | -0.01*** | (0.00) | -0.0806*** | (0.00) |
| Number of children (100s) | -0.61*** | (0.00) | -1.56*** | (0.00) |
| **Immigration** | | | | |
| Immigrated to U.S. 0-5 years ago (dummy) | 0.172*** | (0.00) | 0.594*** | (0.00) |
| Immigrated to U.S. 5-10 years ago (dummy) | 0.093*** | (0.00) | 0.359*** | (0.00) |
| Immigrated to U.S. >10 years ago (dummy) | 0.034*** | (0.00) | 0.159*** | (0.00) |
| **Household Built Environment** | | | | |
| Workers density (million workers/sq. km) | 0.311*** | (0.00) | 1.48*** | (0.00) |
| Bus density (1,000 bus workers/sq. km) | -0.077*** | (0.00) | -0.403*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 0.215*** | (0.00) | -0.156*** | (0.00) |
| Lives in city center (dummy) | 0.004*** | (0.00) | 0.0161*** | (0.00) |
| Lives in rural area (dummy) | 0.012*** | (0.00) | 0.0706*** | (0.00) |

| | | | | |
|---|---|---|---|---|
| Lives in suburban area (dummy) | -0.008*** | (0.00) | -0.0424*** | (0.00) |
| **Workplace Built Environment** | | | | |
| Worker density (million workers/sq. km) | -0.171*** | (0.00) | -1.65*** | (0.00) |
| Bus density (1,000 bus drivers/sq. km) | 0.763*** | (0.00) | 4.11*** | (0.00) |
| Train density (1,000 train workers/sq. km) | -2.33*** | (0.00) | -14.10*** | (0.00) |
| **State-Level** | | | | |
| Log of avg. yearly gas price in state ($2009) | -0.05*** | (0.00) | -0.82*** | (0.01) |
| **State and year fixed effects** | Yes | | Yes | |
| p-value (Pr > F) | 0.0000**** | | 0.0000**** | |
| Observations | 442,178,872 | | 8,346,664 | |

Notes: Standard errors in parentheses. For the probit model, marginal effects are reported. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

## TABLE 1.4: Robustness Checks for General Population Models

| | Drive/No Drive | | | | Carpool/Drive Alone | | | |
|---|---|---|---|---|---|---|---|---|
| | Income Changed (Model 5) | | Heads of HH (Model 6) | | Income Changed (Model 7) | | Heads of HH (Model 8) | |
| | Coeff. | Std. Err. | Coeff. | Std. Err. | Coeff. | Std. Err. | Coeff. | Std. Err. |
| Military in 2000 (dummy) | 0.00722*** | (0.00) | -0.0022 | (0.00) | -0.0235*** | (0.00) | -0.0264*** | (0.00) |
| Military in 2006 (dummy) | 0.0170*** | (0.00) | 0.0110*** | (0.00) | -0.0121*** | (0.00) | -0.0157*** | (0.00) |
| Military in 2007 (dummy) | 0.00361** | (0.00) | -0.0009 | (0.00) | -0.0363*** | (0.00) | -0.0444*** | (0.00) |
| Military in 2008 (dummy) | 0.0490*** | (0.00) | 0.0586*** | (0.00) | -0.0219*** | (0.00) | -0.0196*** | (0.00) |
| Military in 2009 (dummy) | 0.0431*** | (0.00) | 0.0464*** | (0.00) | -0.0219*** | (0.00) | -0.0270*** | (0.00) |
| Veteran (Separated >2 yrs ago) | 0.0257*** | (0.00) | 0.0307*** | (0.00) | -0.0292*** | (0.00) | -0.0273*** | (0.00) |
| Veteran (Separated <2 yrs ago) | 0.0257*** | (0.00) | 0.0137*** | (0.00) | -0.00314*** | (0.00) | -0.00181*** | (0.00) |
| Control variables[ǂ] | Yes | | Yes | | Yes | | Yes | |
| State and year fixed effects | Yes | | Yes | | Yes | | Yes | |
| p-value (Pr > F) | 0.000*** | | 0.000*** | | 0.000*** | | 0.000*** | |
| Observations | 492,338,384 | | 442,701,079 | | 250,270,281 | | 226,174,456 | |

Notes: Standard errors in parentheses. All models are linear probability models. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] I use the following control variables:

**Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, family size, family income, hours worked per week

**Built environment/Other:** employee density of workplace & residence (workers/sq-km), population density of workplace & residence (people/sq-km), train density of workplace & residence (train workers/sq-km), bus density of workplace & residence (bus workers/sq-km), lives in urban environment, lives in rural environment, lives in a suburban environment, state-year log of avg. gasoline price

*1.3.5 Differences between Military and Civilian Populations*

The higher rates of driving and driving alone among military members may contribute to a stronger peer influence among military commuters than civilian commuters because the norms are simply that much stronger. Three factors could explain why military individuals drive to work more than their civilian counterparts even after controlling for individual-level and built environment variables. First, while my set of built environment variables is consistent with those in the travel literature, it is possible that military bases have a unique set of land use characteristics that influence travel behavior and that I do not observe. My land use variables are at the PUMA-level and may lack enough geographic resolution to account for all the transit options and land use configurations in and around military bases. A second explanation is that auto-oriented individuals may self-select into the military. Third, military members may be conditioned to drive and drive alone more often while serving in the military.

I cannot rule out the first explanation but I find evidence for the second or third explanations in the positive signs on the veteran dummy variables. Veterans are individuals who previously served in the military – and were therefore part of the self-selection or conditioning process – but who are no longer affected by land use characteristics of military bases, since presumably most commute to civilian jobs outside of bases. If there is, in fact, a “conditioning process” towards greater driving and driving alone that occurs while an individual works in the military, then this would strengthen the magnitude of the peer influence among military workers. However, without information about the commute decisions of individuals before they entered the military, I cannot say conclusively whether a self-selection or conditioning process explains the higher auto-orientation. What I can conclude is that military members have stronger norms for driving and driving alone after controlling for normal predictors of travel which means that the peer effect among the military may be stronger than the peer effect among civilians.

### 1.4. PEER EFFECTS MODELS

I now examine whether an individual's decision to drive or carpool to work is influenced by the drive or carpool decisions of his or her workplace peers. To determine the impact of workplace peers on one another's travel decisions I consider a military-only sample from bases in which I have 100 or more observations.[15] Table A1 in the Appendix describes the bases in my sample.

My models for the drive and carpool decisions are similar to the respective general population models in the previous section except for two differences: (1) I include an endogenous regressor: the fraction of base workers who drive (drive models) or carpool (carpool models), and (2) I control for regional differences in commute behavior using base-level, rather than state-level, fixed effects.

My linear probability model is:

$$\Pr(I_i = 1) = \beta_o n_i + x_{it}'\beta_1 \tag{3}$$

and my probit model is:

$$\Pr(I_i = 1) = \Phi(\beta_o n_i + x_{it}'\beta_1). \tag{4}$$

The coefficient of interest is $\beta_o$, the coefficient on the fraction $n$ of peers who drive (or carpool). I instrument for the fraction $n$ of peers who drive (or carpool) with the average group demographic variables including the percentage of: American-born individuals, the recent

[15] The cutoff at 100 observations was chosen because we create base-level group average variables as instruments. A secondary selection criteria was that bases could not be located in the same PUMA as another military base since such an arrangement would prohibit us from uniquely identifying an individual's workplace. In total, 58 bases fit my selection criteria (see appendix).

immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. The demographic variables were found to be significant determinants of the drive and carpool decisions in the models in the previous section. Average group demographic variables have been used in past literature as instrumental variables for peer effects models (Manski, 1993) and are appropriate instruments because they predict the percentage of driving or carpooling on a base but are unrelated to whether a given individual chooses to drive or carpool.

The instrumental variables analogs of the linear probability model and the probit model are two-stage least squares and Amemiya generalized least squares, respectively. The Amemiya generalized least squares estimator is formed by first estimating reduced-form parameters and then solving for the structural parameters; this estimator is asymptotically more efficient than a two-stage estimator (Newey, 1987).

### *1.4.1 Peer Effects*

Table 5 gives the first-stage regression results for the drive and carpool models. Each of the instruments is significant at the 0.1% level and both first-stage F-statistics are greater than 7698. Moreover, the instruments for both models pass the Anderson underidentification test and the weak-instrument-robust inference test of joint significance of endogenous regressors, supporting the validity of my instruments.

**TABLE 1.5: First-Stage Regressions**

| | *Dependent variable is:* | | | |
|---|---|---|---|---|
| | *fraction who drive* | | *fraction who carpool* | |
| | **Drive/No Drive** (Model 9) | | **Carpool/Drive Alone** (Model 10) | |
| | Coeff. | Std. Err. | Coeff. | Std. Err. |
| **Instruments** | | | | |
| Percent of base who is U.S.-born | 0.2445*** | (0.00) | -0.240*** | (0.00) |
| Percent of base who immigrated to U.S. 0-5 years ago | 0.2166*** | (0.00) | -0.064*** | (0.01) |
| Percent of base who immigrated to U.S. 6-10 years ago | 0.3001*** | (0.00) | -0.115*** | (0.01) |
| Percent of base who immigrated to U.S. 10+ years ago | 0.225*** | (0.00) | -0.213*** | (0.00) |
| Percent of base born in Latin America | 0.1898*** | (0.00) | 0.0296*** | (0.00) |
| Average age of base (yrs) | 2.0e-4*** | (0.00) | -8.0e-3*** | (0.00) |
| Average family size of workers on base (#) | -3.0e-3 | (0.00) | 6.7e-3*** | (0.00) |
| **Individual** | | | | |
| Age (yrs) | 2.0e-4*** | (0.00) | -1.1e-3*** | (0.00) |
| Age-squared (yrs^2) | -3.8e-6*** | (0.00) | 1.7e-5*** | (0.00) |
| Education (10s of years) | -4.0e-3*** | (0.00) | -1.9e-3*** | (0.00) |
| **Family** | | | | |
| Log of Family Income ($10,000) | 6.0e-4*** | (0.00) | -4.4e-4*** | (0.00) |
| Hours worked per week (100 hours) | -0.021*** | (0.00) | -6.0e-3*** | (0.00) |
| Female employed worker (dummy) | -3.2e-4*** | (0.00) | -5.1e-4*** | (0.00) |
| Family size (100s of people) | -0.067*** | (0.00) | -0.031*** | (0.00) |
| Vehicles per adult in household (number) | -2.1e-4*** | (0.00) | -1.3e-3*** | (0.00) |
| Number of children (100s) | 0.073*** | (0.00) | 0.036*** | (0.00) |
| **Immigration** | | | | |
| Immigrated to U.S. 0-5 years ago (dummy) | -6.6e-5 | (0.00) | -8.9e-4*** | (0.00) |
| Immigrated to U.S. 5-10 years ago (dummy) | -3.7e-5 | (0.00) | -1.7e-3*** | (0.00) |
| Immigrated to U.S. >10 years ago (dummy) | 7.1e-5 | (0.00) | -4.3e-4*** | (0.00) |
| **Household Built Environment** | | | | |
| Workers density (million workers/sq. km) | 1.3e-6*** | (0.00) | 1.95*** | (0.00) |
| Bus density (1,000 bus workers/sq. km) | -0.061*** | (0.00) | -0.64*** | (0.00) |
| Train density (1,000 train workers/sq. km) | -2.80*** | (0.00) | 3.90*** | (0.00) |
| Lives in city center (dummy) | -2.6e-3*** | (0.00) | -2.43e-4*** | (0.00) |
| Lives in rural area (dummy) | -2.6e-3*** | (0.00) | 4.44e-4*** | (0.00) |
| Lives in suburban area (dummy) | -1.8e-3*** | (0.00) | 7.10e-4*** | (0.00) |
| **Workplace Built Environment** | | | | |
| Worker density (million workers/sq. km) | -33.0*** | (0.00) | 88.9e*** | (0.00) |
| Bus density (1,000 bus drivers/sq. km) | 7.40*** | (0.00) | 22.7*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 134.0*** | (0.01) | 171.0*** | (0.01) |
| **State-Level** | | | | |
| Log of avg. yearly gas price in state ($2009) | -2.0e-3*** | (0.00) | -0.034*** | (0.00) |
| Base fixed effects | Yes | | Yes | |
| First-stage F-statistic | 7698.96 | | 8992.97 | |
| First-stage Shea Partial R-squared p-value | 0.000*** | | 0.000*** | |
| Anderson underidentification test p-value | 0.000*** | | 0.000*** | |

| | | |
|---|---|---|
| Weak-instrument-robust inference test of joint significance of endogenous regressions p-value | 0.000*** | 0.000*** |
| p-value (Pr > F) | 0.000**** | 0.0000**** |
| Observations, weighted | 867,480 | 831,195 |

Notes: Standard errors in parentheses. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

Table 6a and 6b present the results from the IV and IV probit models using equations (3) and (4) above, respectively. The probit models are presented as marginal effects at the means. For all models, the coefficient on the endogenous regressors measuring peers' commuting decisions are positive and significant, suggesting that decisions of co-workers to drive and to carpool do in fact influence individuals to do the same. According to the linear probability model for the drive decision (Model 11), if the fraction who drive on a base increases by 0.1, the probability that an individual drives increases by 0.10. According to the linear probability model of the carpool decision (Model 13), if the fraction who carpool on a base increases by 0.1, the probability that an individual carpools increases by 0.04.

The magnitudes of the control variables also suggest that peer influence plays a fairly dominant role in one's commute decisions relative to other factors traditionally associated with travel decisions (Models 12 and 14). For the drive/no drive decision, the most influential variables (listed by magnitude) are: the percentage of peers who drive to base, age, household income, and age-squared. For the carpool/drive alone decision, the most influential variables are age, age-squared, education, and percentage of peers who carpool to base.

The existence and strength of workplace peer influence on commuting is a new finding within the travel literature and suggests that workplace programs that incentivize carpooling and non-auto modes have a positive feedback over time.

**TABLE 1.6a: IV and IV Probit Results for Drive/No drive Decision**

*Dependent variable is probability of driving*

| | Drive/No Drive IV Linear Prob. (Model 11) | | Drive/No Drive IV Probit (Model 12) | |
|---|---|---|---|---|
| | Coeff. | Std. Err. | Coeff. | Std. Err. |
| **Endogenous Variable** | | | | |
| Fraction who drive, by base, year | 1.003*** | (0.03) | 7.155*** | (0.54) |
| **Individual** | | | | |
| Age (yrs) | 6.69e-3*** | (0.00) | 0.0921*** | (0.00) |
| Age-squared (yrs^2) | -9.50e-05*** | (0.00) | -1.30e-3*** | (0.00) |
| Education (10s of years) | -8.45e-3*** | (0.00) | -0.0142*** | (0.00) |
| **Family** | | | | |
| Log of Family Income ($10,000) | 6.57e-3*** | (0.00) | 0.0902*** | (0.01) |
| Hours worked per week (100 hours) | -0.019*** | (0.00) | -0.309*** | (0.00) |
| Female employed worker (dummy) | 6.17e-3*** | (0.00) | 0.107*** | (0.01) |
| Family size (100s of people) | -1.77*** | (0.00) | -15.9*** | (0.00) |
| Vehicles per adult in household (number) | 0.0122*** | (0.00) | 0.254*** | (0.00) |
| Number of children (100s) | 1.90*** | (0.00) | 15.20*** | (0.00) |
| **Immigration** | | | | |
| Immigrated to U.S. 0-5 years ago (dummy) | -0.0319*** | (0.00) | -0.368*** | (0.02) |
| Immigrated to U.S. 5-10 years ago (dummy) | -0.0105*** | (0.00) | -0.191*** | (0.02) |
| Immigrated to U.S. >10 years ago (dummy) | 0.00928*** | (0.00) | 0.120*** | (0.01) |
| **Household Built Environment** | | | | |
| Workers density (million workers/sq. km) | -15.70*** | (0.00) | -90.80*** | (0.00) |
| Bus density (1,000 bus workers/sq. km) | 0.40*** | (0.00) | -8.10*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 27.80*** | (0.00) | 177.0*** | (0.01) |
| Lives in city center (dummy) | 0.0289*** | (0.00) | 0.343*** | (0.01) |
| Lives in rural area (dummy) | -0.0128*** | (0.00) | -0.154*** | (0.01) |
| Lives in suburban area (dummy) | 0.00148*** | (0.00) | 0.0141* | (0.01) |
| **Workplace Built Environment** | | | | |
| Worker density (million workers/sq. km) | 0.959 | (0.00) | 214.0** | (0.00) |
| Bus density (1,000 bus drivers/sq. km) | 0.0422 | (0.00) | -9.61 | (0.03) |
| Train density (1,000 train workers/sq. km) | 188.0*** | (0.08) | -414.0 | (1.73) |
| **State-Level** | | | | |
| Log of avg. yearly gas price in state ($2009) | -5.31e-3*** | (0.00) | 0.0179** | (0.01) |
| Base fixed effects | Yes | | Yes | |
| p-value (Pr > F) | 0.0000**** | | 0.0000**** | |
| Observations, weighted | 867,480 | | 867,480 | |

Notes: Standard errors in parentheses. The fraction on the base who drive is instrumented with the percentage of: American-born individuals, the recent immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. For the probit model, marginal effects are reported. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

**TABLE 1.6b: IV and IV Probit Results for Carpool/Drive Alone Decision**

| | Carpool/Drive Alone IV Linear Prob. (Model 13) | | Carpool/Drive Alone IV Probit (Model 14) | |
|---|---|---|---|---|
| *Dependent variable is probability of carpooling* | | | | |
| | Coeff. | Std. Err. | Coeff. | Std. Err. |
| **Endogenous Variable** | | | | |
| Fraction who carpool, by base, year | 0.407*** | (0.03) | 2.788*** | (0.16) |
| **Individual** | | | | |
| Age (yrs) | -0.0273*** | (0.00) | -0.137*** | (0.00) |
| Age-squared (yrs^2) | 3.44e-4** | (0.00) | 0.00168*** | (0.00) |
| Education (10s of years) | -5.44e-3** | (0.00) | -0.0384*** | (0.00) |
| **Family** | | | | |
| Log of Family Income ($10,000) | -0.0175*** | (0.00) | -0.0899*** | (0.00) |
| Hours worked per week (100 hours) | 0.037** | (0.00) | 0.224*** | (0.00) |
| Female employed worker (dummy) | 0.0480*** | (0.00) | 0.272*** | (0.00) |
| Family size (100s of people) | 1.56*** | (0.00) | 8.99*** | (0.00) |
| Vehicles per adult in household (number) | 0.00519*** | (0.00) | 0.0233*** | (0.00) |
| Number of children (100s) | -1.12*** | (0.00) | -5.47*** | (0.00) |
| **Immigration** | | | | |
| Immigrated to U.S. 0-5 years ago (dummy) | -0.0101*** | (0.02) | -0.0259* | (0.02) |
| Immigrated to U.S. 5-10 years ago (dummy) | 0.000244 | (0.01) | 0.00585 | (0.01) |
| Immigrated to U.S. >10 years ago (dummy) | -0.0137*** | (0.01) | -0.0925*** | (0.01) |
| **Household Built Environment** | | | | |
| Workers density (million workers/sq. km) | 8.11** | (0.00) | 57.90*** | (0.00) |
| Bus density (1,000 bus workers/sq. km) | -3.74** | (0.00) | -27.4*** | (0.00) |
| Train density (1,000 train workers/sq. km) | 3.51*** | (0.01) | 37.1*** | (0.01) |
| Lives in city center (dummy) | 0.00760*** | (0.01) | 0.0457*** | (0.01) |
| Lives in rural area (dummy) | 0.0229*** | (0.01) | 0.148*** | (0.01) |
| Lives in suburban area (dummy) | 0.00308*** | (0.01) | 0.00626 | (0.01) |
| **Workplace Built Environment** | | | | |
| Worker density (million workers/sq. km) | 57.4** | (0.00) | -134.0*** | (0.00) |
| Bus density (1,000 bus drivers/sq. km) | 13.0*** | (0.00) | 53.2*** | (0.02) |
| Train density (1,000 train workers/sq. km) | 969.0*** | (0.08) | 3863.0*** | (0.92) |
| **State-Level** | | | | |
| Log of avg. yearly gas price in state ($2009) | -0.0210*** | (0.01) | -0.180*** | (0.01) |
| Base fixed effects | Yes | | Yes | |
| p-value (Pr > F) | 0.0000**** | | 0.0000**** | |
| Observations, weighted | 831,195 | | 831,195 | |

Notes: Standard errors in parentheses. The fraction on the base who carpool is instrumented with the percentage of: American-born individuals, the recent immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. For the probit model, marginal effects are reported. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

*1.4.2 Interaction Models*

How does the magnitude of the peer effect vary with different characteristics of the individual? I tackle this question by estimating interaction models for the drive and carpool decisions in which I interact the peer effect with various individual-level covariates including income, education level, age, number of years worked in an organization, urban household, number of children, and hours worked per week. These interaction models enable us to examine how the peer effect varies with these covariates.

The interaction models are identical to the linear probability models in Tables 6a and 6b except I interact the endogenous peers' decision variable with the individual-level characteristic (e.g. fraction of workers who drive * individual *i*'s income).[16] A significant coefficient on the endogenous interaction variable indicates that the strength of the peer effect changes with the given variable. For each model, I calculate the "total average effect" of peers, which is the sum of the coefficient on the endogenous peer effect variable and the coefficient on the endogenous interaction variable multiplied by the mean of the interacted variable. All models pass the post-regression weak instrument and underidentification tests.

Table 7a presents the results of the interaction models for the drive decision. In the drive models, the interactions with education level, years in service, and hours worked per week are all significant. For education, the sign is negative indicating that as education level increases, the impact of one's peers decreases, ceteris paribus. One possible explanation is that the more educated an individual, the more likely he or she will make the drive/no-drive decision based on a set of internal reasoning rather than based on group norms.

The interaction on the number of years in the military is positive and significant in the drive model, indicating that a more senior person (defined as serving at least 2 years) in the

[16] Each model also includes a non-interacted endogenous peer effect variable.

military is more affected by his or her peers in the drive to work decision than a junior person (serving two year or less). This is an intuitive result since I expect that the more time one spends in a particular workplace, all else equal, the more likely he or she is to be influenced by norms in that workplace.

The hours worked per week has a negative and significant coefficient in the drive model. Thus, the more hours worked by an individual, the smaller the influence of his or her peers in the drive to work decision. However, it should be noted that when the endogenous variable and endogenous interaction are combined (the "total average effect"), the result is not significant.

Table 7b presents the results of the interaction models for the carpool decision. In the carpool models, the significant interaction variables include: age, urban household, number of children, and hours worked. The coefficient on the age interaction is positive, indicating that the older an individual, the more he or she is influenced by the carpooling decisions of his or her peers.

The coefficient on the urban household interaction is positive, which may result from a stronger "culture" of carpooling in urban areas than in a less-dense suburban or rural environments. Belz and Lee (2012) show that carpooling is more prevalent among urban households than in rural or suburban households, but do not discuss the strength of peer influence in the decision-making process. Owing to data limitations, I am unable to further explore whether residential proximity to other carpoolers leads to higher carpooling rates, but this would be a natural extension of this work and could help determine whether a "critical mass" is needed to stimulate carpooling.

The number of children has a positive sign, indicating that individuals with more children are more influenced by their peers to carpool. Finally, like the drive model, the sign on the hours worked coefficient is negative.

## TABLE 1.7a: Interaction Models for Drive/No Drive Decision

| | *Dependent variable is probability of driving* | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | IV | IV | IV | IV | IV | IV | IV |
| Interaction included | Ln(income) | Education | Age | Nbr yrs in military | Urban | Nbr of Children | Hrs Worked/Wk |
| | (Model 13) | (Model 14) | (Model 15) | (Model 16) | (Model 17) | (Model 18) | (Model 19) |
| Total average effect of fraction who drive | 1.187*** | 1.070*** | 1.197*** | 1.162*** | 1.203*** | 1.166*** | 1.11 |
| | (0.29) | (0.389) | (0.31) | (0.07) | (0.05) | (0.05) | (0.58) |
| Coefficient on fraction who drive | 0.951*** | 1.0727*** | 1.102*** | 0.960*** | 1.231*** | 1.222*** | 2.133*** |
| | (0.22) | (0.283) | (0.23) | (0.06) | (0.04) | (0.04) | (0.41) |
| Coefficient on interaction | 0.16 | -0.004*** | 0.00 | 0.136** | (0.15) | (0.07) | -0.020* |
| | (0.14) | 0.020 | (0.01) | (0.02) | (0.11) | (0.04) | (0.01) |
| Mean value of interacted variable[a] | 1.44 | 13.600 | 30.82 | 1.48 | 0.18 | 0.83 | 51.49 |
| Control Variables[ǂ] | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Base Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First-stage F-statistic for fraction who drive | 5250.56 | 5250.56 | 5250.56 | 5250.56 | 5250.56 | 5250.56 | 5250.56 |
| First-stage F-statistic for interaction variable | 3856.26 | 2544.23 | 4525.65 | 5673.42 | 2604.71 | 1425.28 | 4529.58 |
| First-stage Shea Partial R-squared p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Anderson underidentification test p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Weak-instrument-robust inference test of joint significance of endogenous regressions p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Observations, weighted | 867,480 | 867,480 | 867,480 | 867,480 | 867,480 | 867,480 | 867,480 |
| R-squared (2nd stage) | 0.069 | 1.069 | 0.068 | 0.068 | 0.066 | 0.068 | 0.064 |

Notes: Standard errors in parentheses. The average effect is the coefficient on the fraction who drive plus the mean times the coefficient on the interaction variable. The fraction on the base who drive and its interaction with the given covariate are instrumented with the average group demographic variables including the percentage of: American-born individuals, the recent immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] I use the following control variables:

**Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, family size, family income, hours worked per week

**Built environment/Other:** employee density of workplace & residence (workers/sq-km), population density of workplace & residence (people/sq-km), train density of workplace & residence (train workers/sq-km), bus density of workplace & residence (bus workers/sq-km), lives in urban environment, lives in rural environment, lives in a suburban environment, state-year log of avg. gasoline price

**TABLE 1.7b: Interaction Models for Carpool/Drive Alone Decision**

| | *Dependent variable is probability of carpooling* | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | IV | IV | IV | IV | IV | IV | IV |
| Interaction included | Ln(income) | Education | Age | Nbr yrs in military | Urban | Nbr of Children | Hrs Worked/Wk |
| | (Model 20) | (Model 21) | (Model 22) | (Model 23) | (Model 24) | (Model 25) | (Model 26) |
| Total average effect of fraction who carpool | 0.456 | -1.170 | 0.335 | 0.503*** | 0.412*** | 0.621*** | 0.571 |
| | (0.333) | (1.158) | (0.781) | (0.147) | (0.075) | (0.144) | (0.777) |
| Coefficient on fraction who carpool | 0.20 | -4.052*** | -6.091*** | 0.551*** | 0.316*** | -0.504*** | 2.505*** |
| | (0.244) | 0.811 | (0.559) | (0.127) | (0.067) | (0.099) | (0.563) |
| Coefficient on interaction | 0.180 | 0.3342*** | 0.209*** | -0.031 | 0.530*** | 1.354*** | -0.038*** |
| | (0.157) | (0.061) | (0.018) | (0.050) | (0.189) | (0.127) | (0.010) |
| Mean value of interacted variable[a] | 1.440 | 13.600 | 30.814 | 1.486 | 0.182 | 0.831 | 51.458 |
| Control variables[ǂ] | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Base Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First-stage F-statistic for fraction who carpool | 5548.87 | 5548.87 | 5548.87 | 5548.87 | 5548.87 | 5548.87 | 5548.87 |
| First-stage F-statistic for interaction variable | 4739.48 | 4740.48 | 5036.43 | 10915.92 | 4110.69 | 1574.92 | 5310.95 |
| 1st-stage Shea Partial R2 p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Anderson underidentification test p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Weak-instrument-robust inference test of joint significance of endogenous regressions p-value | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| Observations | 831,195 | 831,195 | 831,195 | 831,195 | 831,195 | 831,195 | 831,195 |
| R-squared (2nd stage) | 0.162 | 0.087 | 0.037 | 0.0651 | 0.162 | 0.092 | 0.0537 |

Notes: Standard errors in parentheses. The average effect is the coefficient on the fraction who carpool plus the mean times the coefficient on the interaction variable. The fraction on the base who carpool and its interaction with the given covariate are instrumented with the average group demographic variables including the percentage of: American-born individuals, the recent immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] I use the following control variables:

**Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, family size, family income, hours worked per week

**Built environment/Other:** employee density of workplace & residence (workers/sq-km), population density of workplace & residence (people/sq-km), train density of workplace & residence (train workers/sq-km), bus density of workplace & residence (bus workers/sq-km), lives in urban environment, lives in rural environment, lives in a suburban environment, state-year log of avg. gasoline price

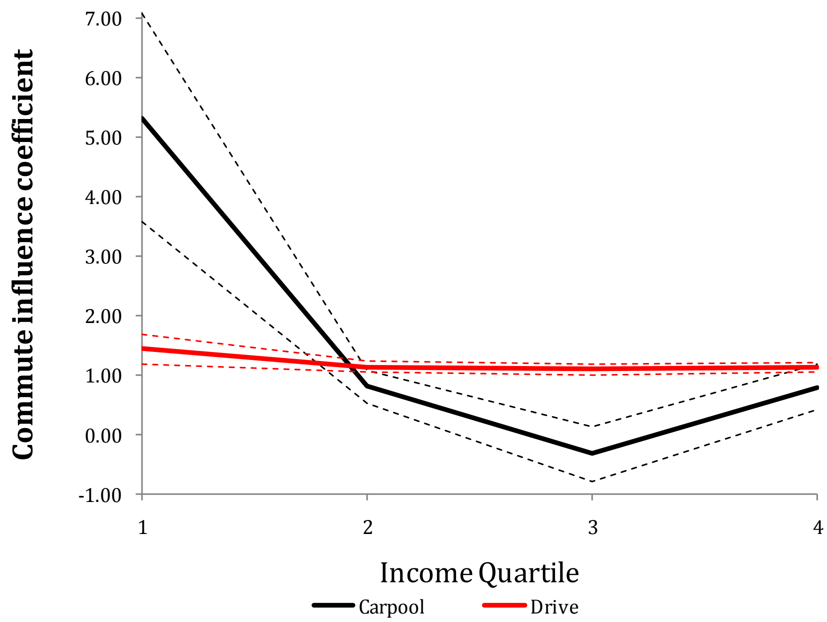
### *1.4.3 Non-Linear Interaction Models*

I also examine if any covariates affect the peer effect non-linearly. In particular, I examine if the peer effect varies non-linearly with income and with the number of children.

Figure 2 plots the peer effects for the drive and carpool decisions, respectively, as functions of income quartile. The slope of the peer effect as a function of income is relatively flat for the drive model which is consistent with the insignificant coefficient on the income interaction in Table 7a. The peer effect in the carpool model deceases with income over the first three income quartiles, suggesting that low income individuals are more likely to be influenced by their peers to carpool than high income individuals are. In the 3$^{rd}$ income quartile, the peer effect is negative which, in conjunction with the positive peer effects in the other income quartiles, likely contributes to the insignificant coefficient on the income interaction in Table 7b.

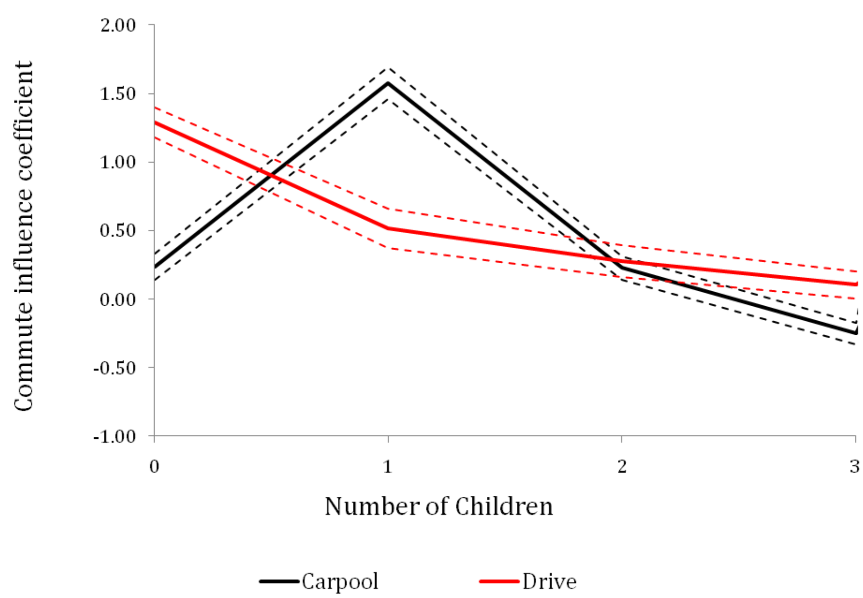
Figure 3 plots the peer effects for the drive and carpool decisions, respectively, as functions of the number of children. The peer effect for the drive decision declines with the number of children. The peer effect for the carpool peaks at 1 child: individuals with one child are more influenced by their peers to carpool than are individuals with 0, 2 or 3 children. Individuals with one child constitute 36% of individuals in the sample while zero-child, two-child, and three-child individuals constitute 29%, 21%, and 12% respectively.

**Figure 1.2. Magnitude of peer effect coefficient by income level.**




Note: Dotted lines indicate the 95% confidence interval.

**Figure 1.3. Magnitude of peer effect coefficient by number of children in household.**




Note: Dotted lines indicate the 95% confidence interval.

*1.4.4 Who Are The Strongest "Influencers?"*

Who exerts the greatest influence on others? According to Cialdini and Trost (1998), authority and social validation are key components of social influence. Authority refers to people who have superior information and power through "knowledge, talent, or fortune" (Cialdini and Trost, 1998, p. 170). Social validation is defined as looking to other individuals – often those similar to oneself – for confirmation that a given action is acceptable (Cialdini and Trost, 1998).

To examine these components of social influence, I break my sample into several sub-groups to test which types of individuals are exerting influence and which types of individuals are being influenced. I use three variables associated with social status (income, age, and education) and one variable related to workplace seniority (number of years in the military). For each of these four variables, I divide individuals on each military base into two groups based on whether they are above or below the mean value of the respective variable. I then examine whether individuals are influenced by those of higher or lower status or workplace seniority, and also whether individuals of the same social status or seniority influence one another.

Based on the theoretical reasoning from Cialdini and Trost (1998), I hypothesize that the greatest social influence should be exerted by: (1) individuals high in social status or workplace seniority on individuals low in social status or workplace seniority (authority); or (2) individuals of the same social status or workplace seniority on one another (social validation). Further, I posit that (3) individuals with low social status or workplace seniority should have no effect or a negative effect on those with high social status or workplace seniority.

Table 8 presents summary statistics of the fraction who drive and the fraction who carpool for each sub-group used in this section. For each variable, I separate individuals into those above the mean and those below the mean. For example, the high income sub-group is composed of individuals whose average family income is more than the mean income of $50,200 per year.

## TABLE 1.8: Summary Statistics of Fraction Who Drive and Fraction Who Carpool by Sub-group

| | | **Drive/No Drive** *Fraction of subgroup who drive* | | | | **Carpool/Drive Alone** *Fraction of subgroup who carpool* | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Subgroup** | **Obs.** | **Mean** | **Std. Dev.** | **Min** | **Max** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| All individuals | 1,672,448 | 0.962 | 0.063 | 0 | 1 | 0.103 | 0.079 | 0 | 1 |
| Higher Income | 657,400 | 0.954 | 0.078 | 0 | 1 | 0.101 | 0.079 | 0 | 1 |
| Lower Income | 1,015,048 | 0.966 | 0.051 | 0 | 1 | 0.105 | 0.079 | 0 | 1 |
| Higher education | 666,127 | 0.956 | 0.076 | 0 | 1 | 0.096 | 0.078 | 0 | 1 |
| Lower education | 1,006,321 | 0.965 | 0.053 | 0 | 1 | 0.108 | 0.080 | 0 | 1 |
| Higher age | 777,001 | 0.958 | 0.070 | 0 | 1 | 0.098 | 0.076 | 0 | 1 |
| Lower age | 895,447 | 0.964 | 0.057 | 0 | 1 | 0.108 | 0.082 | 0 | 1 |
| Senior (> 2 yrs) | 776,907 | 0.962 | 0.059 | 0 | 1 | 0.104 | 0.072 | 0 | 1 |
| Junior (< 2 yrs) | 578,786 | 0.955 | 0.068 | 0 | 1 | 0.097 | 0.079 | 0 | 1 |

Table 9 shows the results of eight linear probability models where the peer effects are broken down by the type of the group exerting influence and the type of the individual being influenced. If I divide both the group exerting influence and the individual being influenced by family income, the highest magnitude of influence is by high income individuals on other high income individuals in both the drive and carpool decisions. The high income group exerts less or no influence on low income individuals. In the drive decision, as hypothesized, the low income group negatively influences high income individuals and low income individuals influence other low income individuals.

If I examine influence by educational level, I again observe positive intragroup influence (e.g. high education individuals influencing other high education individuals) and a positive influence of the high education group on low education individuals for the carpooling decision. However, in contrast to my hypothesis that low status individuals should not influence high status individuals, I find a positive effect of the low education individuals on high education individuals in the drive decision.

Disaggregating the sample by age group also shows positive intragroup influence but has mixed results on intergroup influence. Again, the signs and significance levels of the carpool models seem to better support my hypotheses than those of the drive models.

Finally, a seniority-based metric for authority – serving greater or less than two years in the military – yields mixed results. The intragroup influence has the largest magnitude coefficients in the drive model but has a negative sign for the effects of junior personnel on junior personnel in the carpool model. The carpool model also has a large positive sign on the junior group exerting influence on the senior group – a counterintuitive finding.

In sum, the intragroup influence appears to be stronger and more consistent than intergroup influence. This suggests that, within the realm of driving and carpooling decisions, social validation is a stronger motivator towards conformity than authority.

**TABLE 1.9: Peer Effects by Characteristics of Individuals and Their Peers**

| | | Drive/No Drive | | Carpool/Drive Alone | |
|---|---|---|---|---|---|
| **Group exerting influence** | **Individual being influenced** | **Coef.** | **Std Error** | **Coef.** | **Std Error** |
| Higher income | Higher income | 1.2941*** | (0.05) | 0.9589*** | (0.10) |
| Higher income | Lower income | 0.0282 | (0.02) | 0.3300*** | (0.09) |
| Lower income | Higher income | -0.162** | (0.05) | -0.060 | (0.07) |
| Lower income | Lower income | 1.0497*** | (0.06) | 0.0959 | (0.09) |
| Higher education | Higher education | 0.8788*** | (0.17) | 1.2690*** | (0.20) |
| Higher education | Lower education | 0.1024 | (0.09) | 1.1354*** | (0.11) |
| Lower education | Higher education | 0.4464** | (0.15) | -0.456*** | (0.13) |
| Lower education | Lower education | 0.9389*** | (0.17) | 0.1648** | (0.06) |
| Higher age | Higher age | 0.8804*** | (0.10) | 1.0186*** | (0.31) |
| Higher age | Lower age | 0.2303*** | (0.06) | -0.248* | (0.12) |
| Lower age | Higher age | 0.2518*** | (0.08) | -0.025 | (0.29) |
| Lower age | Lower age | 0.9271*** | (0.10) | 1.0468*** | (0.14) |
| Senior | Senior | 0.7213*** | (0.04) | 0.5348** | (0.19) |
| Senior | Junior | -0.659*** | (0.13) | 0.2227*** | (0.05) |
| Junior | Senior | -0.031*** | (0.01) | 5.3157*** | (0.91) |
| Junior | Junior | 1.8455*** | (0.15) | -4.848*** | (0.76) |

Notes: Standard errors in parentheses. The endogenous variables are instrumented with the average group demographic variables including the percentage of: American-born individuals, the recent immigrants (within the last 0-5 years), immigrants 6-10 years ago, immigrated to U.S. greater than 10 years ago, born in Latin America, average age, and average family size. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.
I use the following control variables:
**Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, family size, family income, hours worked per week
**Built environment/Other:** employee density of workplace & residence (workers/sq-km), population density of workplace & residence (people/sq-km), train density of workplace & residence (train workers/sq-km), bus density of workplace & residence (bus workers/sq-km), lives in urban environment, lives in rural environment, lives in a suburban environment, state-year log of avg. gasoline price, base fixed effects

## 1.5. CONCLUSION

There appears to be overwhelming evidence that workplace peers influence one another's work commute mode decisions on U.S. military bases. Whether this effect is true in civilian workplaces or in other countries is not addressed directly here, although a number of notable differences in travel preference and population demographics exist between civilian and military commuters. Regardless, this paper is the first to show that driving and carpooling norms in the pool of commuters at a given worksite influence individual commuter decisions.

Using instruments to address the endogeneity of the decisions of one's workplace peers, I find that workers are influenced by their peers in both the drive/no-drive decision and the carpool/drive alone decision. According to the linear probability model for the drive decision, if the fraction who drive on a base increases by 0.1, the probability that an individual drives increases by 0.10. According to the linear probability model of the carpool decision, if the fraction who carpool on a base increases by 0.1, the probability that an individual carpools increases by 0.04.

Among all military commuters, individuals with more years in the military service, lower education, and fewer hours worked per week are most highly influenced by peers in the drive/no-drive decision. For the carpool/drive-alone decision, the peer influence is strongest among older individuals with high education, who work fewer hours per week, and who live in urban areas.

I also explore whether conventional measures of social status and seniority (i.e. income, education, age, number of years in the military) predict who exerts the strongest influence on others. I find that individuals of the same level of social status or seniority exert the strongest influence on each other and find less evidence that higher status individuals exert influence on lower status individuals. This suggests that, within the realm of driving and carpooling decisions, social validation is a stronger motivator towards conformity than authority.

In the past 30 years, a number of innovative workplace programs have been implemented to encourage pro-environmental behavior among workers (Carrico and Riemer, 2011). Case studies and empirical experiments that look at shifting commute modes is a subset of this literature and focus on the role of parking charges, workplace training, carpooling incentives, and public transit subsidies (Cambridge Systematics, 1994; Cairns et al., 2010). Cairns et al. (2010) show that reductions in driving of up to 18% have been observed in well-organized commute programs in the UK. My research suggests that once these programs shift the norms at a workplace towards carpooling or non-auto modes, there will be a positive feedback because of the peer effects.

There are two possible mechanisms that could explain why intragroup influences are stronger and more consistent than intergroup influence. First, individuals within the same social group are better able to educate one another because they are seen as more trustworthy and can better capture the attention of those in the same group than a superior (Buller et al., 2007). Second, according to Festinger's (1954) Theory of Social Comparison, when objective evidence is not present, I use similar others for the basis of comparison. It follows that – at least in some domains -- injunctive and descriptive norm transmission occurs most strongly within similar social groups than from higher status to lower status groups.

Trips to and from the workplace account for 27% of vehicle miles travelled (VMT) in light duty vehicles in the United States (FHWA, 2011). Our ability to shift workers towards non-auto modes rests, in part, in understanding which groups of workers most strongly influence others and, similarly, which groups are most influenced by others. Extension of this work to civilian workplaces is a logical next research direction. Additionally, greater insight into the social mechanisms of workplace peer influence on commuting behavior could be achieved through controlled experiments among co-workers. In particular, the success of workplace interventions may rest on research that explores which individuals or subgroups exert the greatest influence on others.

## 1.6. REFERENCES

Belz, N.P., Lee, B.H. 2012. Composition of vehicle occupancy for journey-to-work trips: evidence of ridesharing from 2009 National Household Travel Survey Vermont Add-On Sample. Transportation Research Record: Journal of the Transportation Research Board. No.2322, pp. 1-9.

Bento, A.M., Cropper, M.L., Mobarak, A.M., Vinha, K. 2005. The effects of urban spatial structure on travel demand in the United States. The Review of Economics and Statistics, 87, pp. 466-478.

Brock, W., Durlauf, S., 2001. Discrete choice with social interactions. Review of Economic Studies 68, 235–260.

Brock, W., Durlauf, S., 2002. A multinomial choice model of neighborhood effects. American Economic Review 92 (2), 298–303.

Cairns, S., Newson, C., and A. Davis. 2010. Understanding successful workplace travel initiatives in the UK. Transportation Research Part A 44, pp. 473-494.

Carrasco, J.A., Hogan, B., Wellman, B., Miller, E.J., 2008. Collecting social network data to study social activity–travel behavior: an egocentric approach. Planning and Design, 35, pp. 961-980.

Carrico, A.R., and M. Riemer. 2011. Motivating energy conservation in the workplace: An evaluation of the use of group-level feedback and peer education. Journal of Environmental Psychology, Vol 31, pp. 1-13.

Cervero R. and B. Griesenbeck. Factors influencing commuting choices in suburban labor markets: a case analysis of pleaston, CA. Transportation Research, Part A. Vol. 22 No. 3 1988, pp. 151-161.

Cervero, R. and Kockelman, K. 1997, Travel demand and the 3Ds: density, diversity, and design. 2, pp. 199-219.

Chatman, D. 2003, How Density and Mixed Uses at the Workplace Affect Personal Commercial Travel and Commute Mode Choice, Transportation Research Record, 1831, pp. 193-201.

Cialdini, R.B., Trost, M.R. 1998. Social influence: social norms, conformity, and compliance. In The Handbook of Social Psychology, ed. DT Gilbert, ST Friske, G. Lindzey, 2:151-92. Boston: McGraw-Hill. 4th ed.

Collura, J. Evaluating Ride-Sharing Programs: Massachusetts' Experience. Journal of Urban Planning and Development, Vol. 120, No. 1, 1994, pp. 28–47.

Department of Energy, 2013. Annual Energy Outlook. http://www.eia.gov/oiaf/aeo/tablebrowser/

Dugundji, E.R., Walker, J.L. 2005. Discrete choice with social and spatial network interdependencies. Transportation Research Record: Journal of the Transportation Research Board. No. 1921, pp. 70-78.

Dunivin, K.O. 1994. Military culture: change and continuity. Armed forces and society 20, no. 4: pp. 531-47.

Dumas, J.S., Dobson, R. 1978. Linking consumer attitudes to bus and carpool usage. Transportation Research, 13A, pp. 417-423.

Dunphy, R., Fisher, K., 1996. Transportation, congestion, and density: new insights. Transportation Research Record 1552,pp. 89-96.

Ferguson, E. The influence of employer ridesharing programs on employee mode choice. Transportation, Vol. 17, no. 2, 1990, pp. 179-207.

Goetzke, Frank. 2008. "Network Effects in Public Transit Use: Evidence from a Spatially Autoregressive Mode Choice Model for New York." Urban Studies 45 (2): 407–417.

Grinblatt, M., Keloharju, M., Ikaheimo, S. 2008. Review of Economics and Statistics, 90, pp. 735-753.

Heinen, E. Maat, K., van Wee, B. 2011. The role of attidues toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transportation Research Part D, 16 pp. 102-109.

Heres-Del-Valle, D. Neimeier, D. 2011. CO2 emissions: Are land-use changes enough for California to reduce VMT? Specification of a two-part model with instrumental variables. Transportation Research Part B, 45, pp. 150-161.

Lovejoy, K. Handy, S. 2011. Social networks as a source of private-vehicle transportation: the practice of getting rides and borrowing vehicles among Mexican immigrants in California. Transportation Research Part A, pp. 248-257.

Manski, C. 1993. Identification of endogenous social effects: the reflection problem. Review of Economics and Statistics, 60, pp. 531-42.

McDonald, N. 2007 Travel and the social environment: evidence from Alameda Country, California. Transportation Research Part D Vol 12 pp. 53-63.

Morency, C. The Ambivalence of Ridesharing. Transportation, Vol. 34, No. 2, 2007, pp. 239–253.

Newey W. Efficient estimation of limited dependent variable models with endogenous explanatory variables. Journal of Econometrics 1987; 36; 231-250.

Newson, C., 2002. Making Travel Plans Work: Lessons from UK Case Studies. Department for Transport, London.

Páez, Antonio, and Darren M. Scott. 2005. “Social Influence and the Decision to Telecommute: A Simulation Example.” In *84th Transportation Research Board Annual Meeting, Washington, DC*, 9–13. http://sciwebserver.science.mcmaster.ca/~paezha/Publications/Forthcoming_contributions/Socia_Influence_and_Telecommuting_TRB_v1.1.pdf.

Ruggles, S., J.T. Alexander, K. Genadek, R. Goeken, M.B. Schroeder, and M. Sobek, “Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database],” University of Minnesota, Minnesota, 2010.

Salancik, G., Pfeffer,J. 1977. An examination of need-satisfaction models of job attitudes. Administration Science Quarterly, 22, 427-456.

Steiner, R. "Residential Density and Travel Patterns: A Review of the Literature," Transportation Research Record, 1466 (1995), pp. 37-43.

Tsao, H. S., and D.-J. Lin. Spatial and Temporal Factors in Estimating the Potential of Ride-Sharing for Demand Reduction. Institute.

Vanoutrive, T., van de Vijver, E., van Malderen, L, Jourquin, B., Thomas, I. Verhetsel, A., Witlox, F., What determines carpooling to workplaces in Belgium: location, organization, Journal of Transport Geography, 22, pp. 77-86.

Walker, J. Ehlers, E., Banerjee, I., Dugunji, E. 2011. Correcting for endogeneity in behavioral choice models with social influence variables, Transportation Research Part A, 45, pp. 362-374.

Wilton, R.D. Paez, A., Scott, D.M. 2011. Why do you care what other people think? A qualitative investigation of social influence and telecommuting. Transportation Research Part A, 45, pp. 269-282.

Zhang, M. 2004. The role of land use in travel mode choice: evidence from Boston and Hong Kong. 70, pp. 344-360.

## APPENDIX FOR ESSAY ONE

**Table 1.A1: Military Bases in Sample**

| Base | State | Observations | Area of Base (sq. km) | Workers on Base (#) |
|---|---|---|---|---|
| Maxwell Gunter | AL | 231 | 12 | 4,606 |
| Fort Rucker | AL | 298 | 31 | 7,428 |
| Little Rock Air Force Base | AR | 296 | 294 | 7,257 |
| MC Air Station Yuma | AZ | 236 | 140 | 4,049 |
| Coronado North Island SDNAVSTA Point Loma | CA | 1845 | 2,684 | 51,435 |
| Pendleton SDMCTC | CA | 1182 | 102 | 52,497 |
| Travis Air Force Base | CA | 294 | 369 | 7,676 |
| Peterson Schriver | CO | 390 | 592 | 8,199 |
| Fort Carson | CO | 505 | 37 | 20,183 |
| Jacksonvill Mayport | FL | 788 | 835 | 23,000 |
| MacDill Air Force Base | FL | 211 | 312 | 7,125 |
| Tyndall Air Force Base | FL | 215 | 42 | 4,657 |
| Naval Submarine Base Kings Bay | GA | 231 | 97 | 5,637 |
| Robins Air Force Base | GA | 210 | 663 | 18,206 |
| Fort Benning | GA | 215 | 44 | 31,698 |
| Fort Gordon | GA | 236 | 72 | 16,160 |
| Naval Station Pearl Harbor | HI | 571 | 682 | 19,892 |
| Hickam Air Force Base | HI | 303 | 813 | 8,309 |
| Schofield Shafter | HI | 561 | 298 | 19,517 |
| Fort Riley | KS | 303 | 53 | 16,653 |
| Fort Campbell | KT | 533 | 204 | 31,809 |
| Fort Knox | KT | 320 | 42 | 18,423 |
| Fort Polk | LA | 296 | 25 | 10,319 |

| | | | | |
|---|---|---|---|---|
| Andrews Air Force Base | MD | 219 | 410 | 8,294 |
| Offutt Air Force Base | NE | 218 | 988 | 7,646 |
| Nellis Air Force Base | NV | 397 | 411 | 8,674 |
| McGuire Air Force Base | NJ | 254 | 493 | 7,185 |
| Fort Drum | NY | 463 | 45 | 19,378 |
| Pope Air Force Base | NC | 205 | 3,897 | 3,362 |
| Seymour Johnson Air Force Base | NC | 228 | 362 | 4,731 |
| Fort Bragg | NC | 1064 | 90 | 55,501 |
| MCAS Cherry Point | NC | 220 | 195 | 10,387 |
| MCB Camp Lejune | NC | 925 | 14 | 48,210 |
| Wright-Patterson Air Force Base | OH | 257 | 911 | 14,434 |
| Beaufort Parris Island | SC | 216 | 122 | 6,743 |
| Dyess Air Force Base | TX | 210 | 429 | 5,427 |
| Lackland Randoph | TX | 786 | 1,633 | 22,063 |
| Fort Sam Houston | TX | 311 | 1,530 | 19,735 |
| Fort Bliss | TX | 335 | 27 | 21,626 |
| Fort Hood | TX | 1356 | 66 | 55,834 |
| Naval Station Norfolk | VA | 1646 | 3,593 | 52,101 |
| Little Creek Oceana | VA | 758 | 1,891 | 22,360 |
| Portsmith Hospital | VA | 286 | 13,609 | 6,063 |
| Langley Air Force Base | VA | 370 | 757 | 11,559 |
| Fort Myer | VA | 290 | 2,387 | 2,349 |
| Naval Base Kitsap Bremerton | WA | 467 | 675 | 21,364 |
| Fort Lewis | WA | 623 | 100 | 34,207 |
| **Sum** | | 21,630 | 42,333 | 863,224 |
| **Average Size** | | 460 | 901 | 18366 |

Notes: All bases have at least 100 observations. Average number of observations per base is 460. Average size of base is 901 sq. km and 18,366 personnel.

**TABLE 1.A2: Two Sample t-Tests of Veterans and Civilian Worker Populations (2000, 2006-2009 ACS)**

| Sample size (weighted) | **Civilian Workers** n =9,860,327 (591,899,750) | | | | **Veteran Workers** n = 953,079 (47,124,493 ) | | | | **Sig** |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min | Max | Mean | Std. Dev. | Min | Max | |
| **Commute** | | | | | | | | | |
| Drive to work (dummy) [alternatives are bus, train, ferry, taxi, walk, cycle, work at home, other] | 0.89 | 0.31 | 0 | 1 | 0.91 | 0.28 | 0 | 1 | *** |
| Carpool (dummy) [alternative is to drive alone] | 0.20 | 0.30 | 0 | 1 | 0.10 | 0.30 | 0 | 1 | *** |
| **Socio-economic / Demographic** | | | | | | | 0 | 0 | |
| Age (years) | 39.39 | 12.19 | 17 | 61 | 46.41 | 10.47 | 17 | 61 | *** |
| Education level (years) | 13.50 | 2.54 | 4 | 21 | 13.50 | 2.02 | 4 | 21 | *** |
| **Family** | | | | | | | 0 | 0 | |
| Family income ($10,000) | 6.65 | 6.06 | -3.1 | 137 | 6.89 | 5.58 | -3.1 | 137 | *** |
| Hours worked per week (hours) | 39.90 | 11.89 | 1 | 99 | 43.73 | 11.08 | 1 | 99 | *** |
| Female employed worker (dummy) | 0.10 | 0.31 | 0 | 1 | 1.09 | 0.29 | 0 | 1 | *** |
| Family size (number) | 2.69 | 1.49 | 1 | 31 | 2.68 | 1.43 | 1 | 21 | *** |
| Vehicles per adult in household (number) | 1.25 | 0.69 | 0.05 | 6 | 1.30 | 0.66 | 0.08 | 6 | *** |
| Number of children (number) | 0.56 | 0.93 | 0 | 9 | 0.79 | 1.08 | 0 | 9 | *** |
| **Immigration** | | | | | | | 0 | 0 | |
| Immigrated to US 0-5 years ago (dummy) | 0.02 | 0.13 | 0 | 1 | 0.003 | 0.05 | 0 | 1 | *** |
| Immigrated to US 5-10 years ago (dummy) | 0.02 | 0.15 | 0 | 1 | 0.003 | 0.05 | 0 | 1 | *** |
| Immigrated to US >10 years ago (dummy) | 0.08 | 0.30 | 0 | 1 | 0.05 | 0.21 | 0 | 1 | *** |

Notes: For each variable, a two-sample t-test was conducted to compare the military population with the non-military population. The "Sig" column reports the significance levels from the test. .Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

**TABLE 1.A3: Two Sample t-Tests of Veterans and Civilian Built Environments (2000, 2006-2009 ACS)**

| | Civilian Workers n =9,860,327 (591,899,750) | | | | Veteran Workers n = 953,079 (47,124,493 ) | | | | Sig |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std Dev. | Min | Max | Mean | Std Dev. | Min | Max | |
| **Residential PUMA** | | | | | | | | | |
| Employment density (workers/sq. km) | 1,755 | 6399 | 0.2 | 156,495 | 685 | 1132. | 1.56 | 17 | *** |
| Bus density (bus workers/sq. km) | 7.1 | 19.81 | 0 | 317 | 2.225 | 3.635 | 0.01 | 82 | *** |
| Train density (train workers/sq. km) | 0.29 | 1.56 | 0 | 25 | 0.05 | 0.28 | 0 | 6.0 | *** |
| Lives in city center (dummy) | 0.15 | 0.36 | 0 | 1 | 0.18 | 0.38 | 0 | 1 | *** |
| Lives in rural area (dummy) | 0.16 | 0.34 | 0 | 1 | 0.11 | 0.31 | 0 | 1 | *** |
| Lives in suburban area (dummy) | 0.35 | 0.44 | 0 | 1 | 0.24 | 0.42 | 0 | 1 | *** |
| Lives in metropolitan area, land use type not specified (dummy) | 0.34 | 0.47 | 0 | 1 | 0.46 | 0.49 | 0 | 1 | *** |
| **Workplace PUMA** | | | | | | | | | |
| Employment density (workers/sq. km) | 3,360 | 15,135 | 0.2 | 156,495 | 872 | 168 | 16.2 | 12 | *** |
| Bus density (bus workers/sq. km) | 10.4 | 33.67 | 0 | 317 | 2.7 | 4.42 | 0.05 | 22 | *** |
| Train density (train workers/sq. km) | 0.52 | 2.67 | 0 | 25 | 0.08 | 0.25 | 0 | 0.9 | *** |

Notes: For each variable, a two-sample t-test was conducted to compare the military population with the non-military population. The "Sig" column reports the significance levels from the test. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

ESSAY TWO

Short-Run Effects of Rapid Employment Growth on Travel Time to Work:

An Empirical Analysis using Military Troop Movements

## 2.1 INTRODUCTION

Employment growth is a common public policy goal, but it can lead to a number of unwanted environmental, social, and economic costs – particularly in high growth communities – due to its impact on peak-hour traffic. Some have shown that traffic congestion is the number one concern of individuals in rapidly growing areas in the U.S., often ranked higher than crime, school over-crowding, and housing shortages (Cervero, 1989; NJ, 2005; GAO, 2009). Congestion is undesirable because it discourages future economic growth (Hymel, 2009; Sweet, 2011), increases vehicular emissions, increases fuel expenses, decreases economies of agglomeration, heightens the psychological burden of travel, creates a need for more emergency services, and imposes an opportunity cost on time (Downs, 1992; Downs, 2004). Over the past three decades, employment growth rates (measured in the annual percentage change in the number of employed individuals per square kilometer) have averaged 1.4% per year in the U.S.; some high growth communities like the city of Las Vegas in the 1990s or Atlanta in the 2000s reached employment growth rates of over 10% per year (Ruggles et al., 2012). Anecdotal evidence suggests that rapid employment growth and congestion are linked. This paper attempts to measure the strength of this relationship.

Here, travel time is used (rather than a congestion index) to measure the impact of employment growth because it allows the use of person-level data. Additionally, despite being a simple concept in practice, traffic congestion is difficult to measure because of its heterogeneous nature across space and time (Downs, 2004). The most well-known measure of congestion is the Travel Time Index developed by the Texas Transportation Institute which is the travel time of a certain route during peak-hour traffic divided by the travel time in free-flow traffic. Some organizations have criticized TTI's congestion index because of its inability to measure congestion on all routes and because it fails to account for certain travel demand management strategies like ramp metering and advanced signaling (Downs, 2004).

Travel time is a measure of both the speed (i.e. congestion) and distance of travel. In the short run, the employment growth forecasted by transportation planners often differs from actual growth leading to inaccurate travel models (Rodier et al., 2002), mismatches between infrastructure supply and demand, and sometimes higher levels of traffic congestion. In the longer run, after infrastructure has time to adjust for example through the construction of new roads, growth affects the speed and distance of travel by re-organizing relative locations of jobs and housing (Gordon, 1989). Whether this re-organization increases or decreases travel times depends on the specific spatial makeup of the region. The focus of this paper is on the short-run, congestion-related effects of employment growth, not the longer-run, jobs-housing distance effect.

A number of well-studied factors, other than employment growth, also affect travel times to work. These include micro-, congestion-related factors like inclement weather, traffic accidents, special events, and road construction as well as macro factors which affect congestion or distance of travel like absolute employment level (larger metropolitan areas tend to have higher travel times); infrastructure expansion/contraction; vehicle ownership; travel preferences (e.g. mode shifts); geo-demographics; number of two-worker households; and the spatial structure of the region (FWA, 2012; Downs, 2004). Additionally, any factor that affects traffic congestion will be dampened by the "triple convergence" in which commuters re-adjust to a new steady-state by switching routes, modes, and departure times (Downs, 1992; Choo and Mokhtarian, 2008).

Traffic congestion has been described as a "creeping crisis" because so many of the macro factors listed above evolve over extremely long timeframes (Downs, 2004). For most factors, this long timeframe means transportation planners have sufficient time to react with effective anti-congestion measures. However, fluctuations in employment can occur at a rapid pace, making the implementation of anti-congestion measures extremely difficult.[17]

Measuring the effect of rapid employment growth on travel time requires separating out these many factors and isolating the impact of employment growth. Most notably, a simultaneity problem arises because an increase in congestion reduces the attractiveness of a community to potential new firms which, in turn, reduces the number of future commuters using the transportation network (Hymel, 2009; Sweet, 2011). Potential new residents and businesses are incentivized to either locate on the outskirts of the city or in another city altogether (Downs, 1992). A second endogeneity problem stems from omitted variables (such as transportation infrastructure) that are related to both employment growth and travel time. Many congestion researchers have suggested that higher growth is associated with worsening traffic but have not empirically estimated the relationship or dealt with the endogeneity problems (Freilich and White, 1991; Downs, 2004).

This paper examines how rapid increases in regional employment affect travel time to work by exploiting exogenous variation resulting from movements of military troops during the 2005 Base Realignment and Closure (BRAC) process to address the endogeneity of employment

[17] There is also empirical support for the fundamental law of road congestion, which states that even if transportation planners increased the provision of roads and transportation infrastructure, this is unlikely to relieve congestion on these roads (Duranton and Turner, 2011).

growth. The BRAC process provides a convenient quasi-experimental framework to measure the short-term, congestion-related effects of employment growth on travel times because it occurred exogenous to the normal transportation planning process[18]. I only consider bases and communities that received troops in the 2005 BRAC, and briefly discuss the impact on bases that were closed. I conduct two separate analyses to measure the short-term, congestion-related effects of employment growth on travel time to work. The first uses difference-in-difference (DD) and difference-in-difference-in-difference (DDD) methods in which travel times for BRAC-affected individuals are compared to travel times for non-BRAC-affected individuals both before and after the 2005 BRAC. This is done for both a military-only subgroup and a larger, civilian and military sub-group. In the second analysis, I use an instrument variable (IV) model in which I instrument for regional employment density growth using the number of individuals gained in the 2005 BRAC. The number of troops gained for each area ranges from 1,200 troops to 28,000 troops over the five-year period and corresponds to annual growth rates in employment density (in workers per square kilometer) of 0.01-7.0%. The IV method enables measurement of a causal relationship between employment density growth and travel time. Results are quite robust – each additional commuter added to the network per square kilometer adds 0.0032-0.055 additional minutes of travel for all other commuters in the short run.

A better understanding of the relationship between employment growth and travel times would help policymakers develop effective anti-congestion growth measures. Additionally, such an understanding would assist travel modelers evaluate acceptable tolerances of errors between the predicted and actual growth in their transportation models. At a more specific level, this

[18] The simultaneity and omitted variable endogeneity problems are addressed by these exogenous troop movements. However, as explained below, one additional endogeneity problem persists: the selection criteria used by the Department of Defense to choose bases for the 2005 BRAC included consideration of community transportation infrastructure. However, this likely results in dampening, not strengthening, the effect measured here.

paper contributes to our understanding of how military troop movements affect communities around military bases. Traffic congestion is a major concern near military bases (Norfolk, 2007; NAS 2012) and no academic study has looked at how the movements of troops – either from base closures or from routine deployment cycles – affect a region's transportation network. Major fluctuations in the number of troops at domestic bases are expected in the next decade because of: 1) reductions to the Department of Defense's budget, 2) the return of many of troops from foreign bases, and 3) another round of base closures expected in 2015.

## 2.2 EXOGENEITY OF THE 2005 BRAC

Here, I address potential endogeneity problems in measuring the impact of employment growth on travel time. As discussed above, a simultaneity problem would exist if the travel time had an influence on employment growth. Omitted variable problems would exist if there were factors related to both the movement of troops and to changes in travel time. I identify two potential omitted variable problems: 1) the BRAC decisions could be based, at least to some degree, on the existing transportation infrastructure and 2) BRAC-affected communities may have taken pre-emptive or concurrent action to upgrade or expand their transportation infrastructure before or during the movement of troops. I first discuss the omitted variable problems then the simultaneity problem.

To contextualize the discussion, a brief history of the BRAC process and the 2005 BRAC is given. In the 2005 BRAC, the Department of Defense (DoD) closed 29 bases and relocated 123,000 troops to 57 other bases in a process known as Base Realignment and Closure (BRAC). These 123,000 troops relocated over a relatively short period (between 2006 and 2011). Since the end of the Cold War, there have been five rounds of base closures (1989, 1991, 1993, 1995, and

2005) with the primary goal of reducing the DoD physical infrastructure budget and improving the military's strategic agility. Past rounds of BRAC have closed between 17 and 33 bases and the next round is tentatively scheduled for 2015.

### 2.2.1 Omitted Variable Problems

As in past rounds of BRAC, the decision for which bases to include/exclude in the round of closures in the 2005 BRAC was a mix of political, budgetary, and strategic interests (Beaulier et al., 2011). The first major step in the BRAC process was in May, 2005 when the Secretary of Defense gave the list of recommendations to the BRAC Commission – a group of nine high ranking political and military figures appointed by the President to oversee the process. Of these recommendations, 86% were eventually approved by the Commission and authorized by the President (Beaulier et al., 2011). The DoD used a set of eight criterion to rank potential bases (DoD, 2005). Four criteria relate to how a closing/realignment will add to the ability of the military to accomplish its mission, one relates to the costs and savings of a to the military, another to the environmental impact of a closure or realignment, and another to the economic impact on existing and "receiving" communities (communities that gain troops). The final criterion – impact on community infrastructure – is germane to this study. It considers, "the ability of the infrastructure of both the existing and potential receiving communities to support forces, missions, and personnel (p. 333, DoD, 2005)." Specifically, the infrastructure considerations include transportation, utilities, schools, employment, medical providers, housing availability, and crime.

Thus, the existing transportation system of receiving bases is, at least to some degree, related to the decision to place troops at a base. A logical consequence is that communities that received troops in the 2005 BRAC were larger and had better transportation infrastructure than a randomly chosen military community. However, it should be noted that transportation infrastructure was just one of several factors considered in the movement of troops and was not the sole driver in the selection of one receiving base versus another. Furthermore – and more importantly -- if BRAC communities that received new troops were, on the whole, more able to absorb new commuters, the magnitude of the effect measured here – the impact of growth on travel time to work -- would be dampened. Thus, our reported coefficients may be underestimated.

An omitted variable problem could also exist if communities receiving new troops took action to improve transportation infrastructure before or during the movement of troops began. I think this effect is small because of the condensed timing of events in the 2005 BRAC process. Re-locations of troops in the 2005 BRAC were to begin in January 2006 and finish by September, 2011. As shown in Table 2, not until the spring of 2005 did the Department of Defense submit a list of bases they recommended for closing. Even if a base was on a list, however, did not mean it was guaranteed to be closed. Media reports from the summer of 2005 indicate real estate investors were hesitant to make real estate transactions until the final recommendations were made in September 2005 (Hedgepeth, 2005). Similarly, action by transportation planners would not have begun until November, 2005 when the President approved the final list of base realignments. Thus, planners had a minimum of three months to begin planning for the first troop movements.

**Table 2.2: Timeline of 2005 BRAC Process**

| **Date** | **Action** |
|---|---|
| Dec. 28, 2001 | Congress authorizes DoD to explore options for a 2005 BRAC |

| | |
|---|---|
| Mar. 23 , 2004 | DoD provides troop inventories of all bases to congress |
| Apr. 1, 2005 | Congress appoints 8-member BRAC commission to oversee BRAC process |
| May 16, 2005 | Secretary of Defense submits recommendations of base closures to BRAC commission |
| Sept. 8, 2005 | BRAC commission provides recommendations for realignments to congress |
| Nov. 7, 2005 | President approves BRAC base realignment list |
| Jan. 1, 2006 | Troop relocations begin |
| Sept. 30, 2011 | Deadline for completion of troop movements |

Typically, detailed traffic studies are needed to justify any major transportation infrastructure expansion. These studies are followed by a planning and design phase and then by public discussion. Finally, permitting and construction often takes more than a year unless public safety is a concern. Infrastructure capacity expansion projects are listed on the Metropolitan Planning Organization's Long-Range Transportation Plan which has a planning horizon of 20 years.

A National Academies of Science (2011) report on the 2005 BRAC states that: "The problems for state and local jurisdictions in BRAC cases are attributable to the rapid pace of traffic growth on heavily used facilities….The normal length of time for development of highway and transit projects – from required planning and environmental processes all the way through construction – is, at best, nine years and usually 15 to 20 years" (p. 7, NAS, 2011). The NAS report concludes that the BRAC timeline gave insufficient opportunity for receiving communities to properly conduct transportation planning.

The Washington DC area – a region with numerous BRAC-affected bases – provides an example of the duration of infrastructure improvements. Closely following the final list of base realignments, the Washington DC Metropolitan Planning Organization announced plans to expand I-375 to help facilitate the additional troops at Fort Meade, Maryland. By the deadline for completion of the BRAC process in September, 2011, the additional lanes of highway still had not been added (Washington Post, 2011). Furthermore, in 2011 in response to public criticism towards the BRAC-related traffic congestion, the head of the Washington DC Metropolitan Planning Organization exclaimed "We just don't have the resources to add capacity when they [US Congress] just drop these things [BRAC] out of the sky," (Ron Kirby, 2011).

### 2.2.2 Simultaneity Problems

I feel the 2005 BRAC is free from potential simultaneity problems because of the nature and timing of the BRAC process. The 2005 BRAC occurred as a result of an exogenous, top-down governmental requirement, not as part of a normal employer location decision. In other words, the government did not adjust the number of troops it sent to an area because of increasing levels of congestion. Rather the relationship is unidirectional – congestion increases as more troops move into an area.

A simultaneity problem could also exist if civilian firms changed their location decision because of a community's traffic congestion. Hymel (2009) uses a time series analysis of data from Los Angeles, California to show the effect of traffic-related feedback on employment growth. However, he also shows that the effect is lagged by at least 10 years (i.e. increased traffic congestion dampened employment growth in an area after 10 years). Since I measure the short-run impact of employment growth on traffic congestion over a 6-year period, this feedback is not a problem.

I acknowledge there could also be short-run positive economic feedback between BRAC troop movements and employment levels, whereby the additional troops in a community attract new employment – particularly retail and service jobs. This would inflate the effect observed here because I would be underestimating the number of new employees in a community.

However, this effect is likely lagged as well, though probably less than 10 years[19]. My main effect in this study is demonstrated in the first year of BRAC (2006) suggesting that the effect exists despite these economic feedbacks.

## 2.3 DATA

Using the US military to measure the relationship between employment growth shocks and travel time has a number of benefits. First, the Department of Defense maintains well-kept records on troop levels at its bases. This allows tracking the exact number of employees who commute to each base in each year. Also, the U.S. military is relatively homogenous between bases in its demographic composition meaning BRAC-affected bases gain or lose similar distributions of personnel between bases. Military bases exist in a geographically diverse set of cities and towns allowing the examination of the effect of employment growth shocks on different parts of the country.

There are also disadvantages to using a population of military for this analysis. First, a number of important differences exist between commuting to a military base and commuting to an average workplace. According to 2000-2010 census data, military bases reach peak traffic at 7:45 in the morning and 4:32 in the afternoon while the civilian traffic is at 8:32am and 5:47pm (Ruggles et al., 2012). Therefore, military members commute at slightly off-peak times which would likely lessen a change in travel time due to BRAC. Military commuters also have fewer alternatives to driving than civilians because of lack of public transit, no option to telecommute, and often low density built environment on base[20]. Military also generally have a greater preference for driving to work than their civilian counterparts -- 94% of military commute by

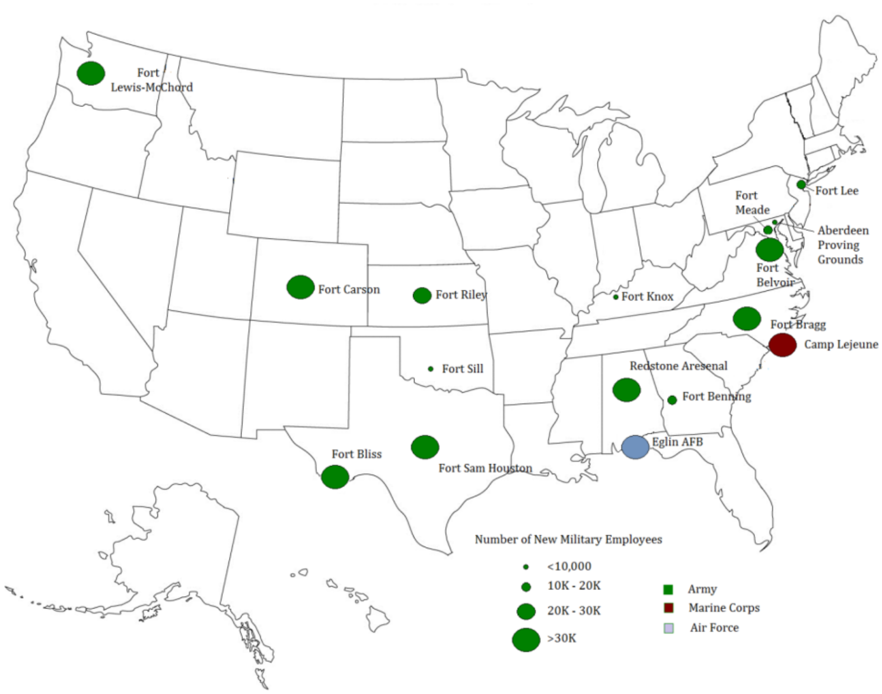
[19] We are unaware of any literature that estimates the lag of this effect.

[20] Data on 85 domestic military bases from DoD (2011) was collected. Military bases have a range of different land use and transit availability.

auto while 89% of civilians commute by auto (Ruggles et al., 2012). A higher drive-to-work rate could have an amplification effect on traffic congestion in the face of employment growth. Also, military commuters must pass through security gates on their way to work. The impact of these gates is not quantified here, although the gates likely amplify the travel delay in congested regions (FHWA, 2004). To partially address the drawbacks of using a military population, the effects of employment growth on travel time to work for both the military population as well as the civilian population who work in areas adjacent to the military bases are analyzed.

For this study, I use the 16 bases and communities whose transportation systems were deemed highly affected by the 2005 BRAC according to a later Government Accountability Office (2009) study (Figure 1). Other bases that gained troops in the 2005 BRAC are not considered because of limitations in the collection of data.

**Figure 2.1: Domestic military bases used in this study (OEA, 2012)**



I use person-level, repeated cross-section data from the 2000 decennial census and the 2005-2010 American Community Surveys (ACS), available through the University of Minnesota's IPUMS website (Ruggles et al., 2010). The years 2001-2004 were the first years of the ACS and are omitted here because they do not include a complete set of variables. One limitation of this dataset is that the geographic location of an individual's residence and workplace are only known within regions containing approximately 100,000 people (called PUMAs). However, for individuals in the military, a combination of their service affiliation (e.g. Air Force, Army, etc.) and their workplace region allows assignment of that individual to a specific military base. For example, individual XX is known to work on Fort Meade, Maryland and live in PUMA YY. This paper only considers military individuals who are commuting from private houses or apartment buildings off-base and omits those who live on-base in barracks or on ships. Data on the number of troops gained by each community come from Table 2 of GAO (2009). The weighted sample sizes used in models in this paper are extremely large, ranging from 265,161 to 29.2 million observations.

Table 1 shows summary statistics of the military BRAC population and the US general population for all variables used in the analysis. Summary statistics for all subgroups considered in the DD(D) and IV analyses are available in table A-1 of the Appendix.

**Table 2.1: Summary statistics of treatment and reference groups used in this analysis.**

| **Variable** | **Min** | **Max** | **Military in BRAC-affected Areas** *Mean (std error)* | **US Average** *Mean (std error)*[1] |
|---|---|---|---|---|
| Commute Travel Time 2000-2005 | 0 | 188 | 20.43 (16.16) | 23.81 (23.17) |
| Commute Travel Time 2006-2010 | 0 | 188 | 22.52 (17.32) | 23.58 (22.13) |
| Worker density (workers/sq-km) | 5.66 | 193.3 | 770.2 (39.20) | 2040.3 (497.40) |
| Age*Age | 289 | 3721 | 1,037 (553.28) | 1,852 (1169.63) |
| Education | 0 | 16 | 7.61 (1.82) | 7.36 (2.31) |
| Family members | 0 | 1 | 2.90 (1.49) | 2.84 (1.60) |

| | | | | |
|---|---|---|---|---|
| Female | 0 | 1 | 0.14 (0.35) | 0.47 (0.50) |
| Family income ($100K) | -0.2 | 17.21 | 59,915 (39,919) | 165,314 (923,530)[1] |
| Immigration status | 0 | 1 | 0.10 (0.29) | 0.17 (0.37) |
| Num. riders in car | 0 | 9 | 1.08 (0.52) | 0.99 (0.70) |
| Hours worked | 0 | 99 | 53.23 (14.50) | 39.46 (12.50) |
| Vehicles per family member | 0 | 6 | 1.15 (0.61) | 1.20 (0.72) |
| Married | 0 | 1 | 0.71 (0.45) | 0.53 (0.50) |
| Population density (people/sq-km) | 11.2 | 340.8 | 86.70 (70.90) | 402.60 (842.10) |
| Lives in rural area | 0.0 | 1 | 0.16 (0.36) | 0.15 (0.36) |
| Lives in urban area | 0 | 1 | 0.13 (0.34) | 0.15 (0.36) |
| Train density (train operators/sq-km) | 0 | 0.36 | 0.015 (0.043) | 0.32 (1.55) |
| Bus density (bus operators/sq-km) | 0.0 | 0.67 | 0.047 (0.090) | 0.91 (3.62) |
| **Sample Size unweighted (weighted)** | | | **6,093 (631,802)** | **9.60E6 (9.81E8)** |

[1] All employed people between 17-61 years old.
[2] Family income should not be confused with per capita income which is much lower for the US. Family income refers to all pre-taxed income by one's family and is likely skewed upwards by high income individuals.

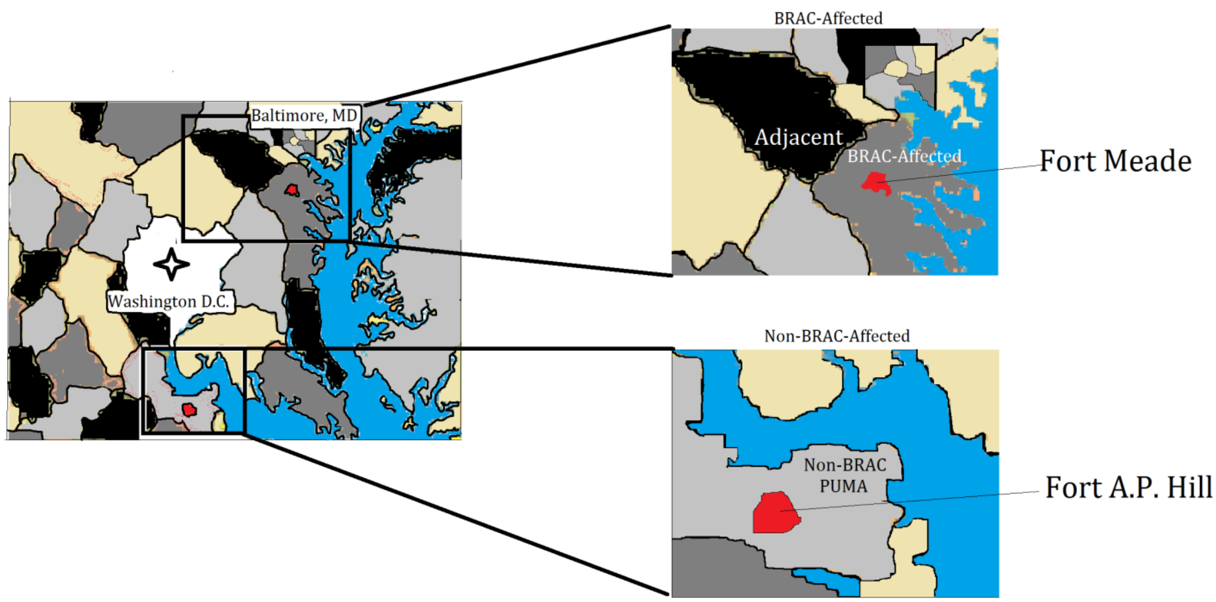
## 2.4 DIFFERENCE-IN-DIFFEREN (-IN-DIFFERENCE) ESTIMATION

I use both difference-in-difference (DD) and difference-in-difference-in-difference (DDD) models with geographic and year fixed effects and a vector of control variables to explore the relationship between employment growth shocks and change in travel time. DD(D) estimations measure the impact of an intervention or policy by comparing the treated group with one (or two in the case of DDD) control group(s) both before the policy and after the policy. I estimate six different DD(D) models, as described below. In all models the policy I consider is the 2005 BRAC.

In the first DD model (DD-1), the treatment group consists of military personnel in the BRAC communities and the control group consists of civilians in the BRAC communities. Using Figure 2 as an example, DD-1 would compare the military members who commute to the BRAC-affected Fort Meade (and the 15 other BRAC-affected bases) with civilians who work in the same BRAC-affected PUMA as Fort Meade, represented by dark grey region surrounding Fort Meade (along with the civilians in the 15 other BRAC-affected PUMAs). A dummy variable is used to distinguish between the pre-BRAC period (2000 and 2005) and post-BRAC period (2006-2010). The advantage of the control group in DD-1 is they share the same geographic area as the BRAC-affected military members, and therefore have similar land-use compositions and transportation infrastructure. However, the disadvantage of this treatment group is that these civilians are also affected by increased traffic congestion caused by the troop re-locations since they work in the vicinity of a BRAC-affected base. If this is true, however, it would mean a significant effect would be more difficult to detect. The second disadvantage is that, as civilians, this control group may not be exposed to policies, traffic regulations, or infrastructure specific to military bases.

The ensure that the control group is not also affected by increased traffic congestion caused by the troop re-locations, the DD-2 model uses as it control group military individuals on non-BRAC affected bases. Again with Figure 2 as an example, DD-2 compares military travel time of workers on Fort Meade (and 15 other treatment bases) with military workers at Fort AP Hill (and 37 non-BRAC-affected bases total). The advantage of this controls group is that it controls for military-specific factors that affected commute travel in the years 2000-2010. The disadvantage of this control group is that these individuals may be influenced by different set of city-level factors such as land-use, weather, transit availability, etc. since these bases are located in other regions of the country.

**Figure 2.2.** Examples of treatment and comparison groups in DD(D) models near Washington D.C. Military bases shown in red. Fort Meade gained 28,000 new workers as a result of the 2005 BRAC. Fort A.P. Hill neither gained nor lost workers in the BRAC.




Since both DD-1 and DD-2 have advantages and disadvantages, a third model (DDD-1) is estimated which uses the control groups from both models. This model differences out both changes in travel time experienced by civilians in the BRAC communities as well as changes in travel time experienced by military individuals on non-BRAC affected bases. It thus controls for factors that affect both military and non-military members in the same PUMAs as well as factors affecting military members on all bases, allowing us to identify the effect of the BRAC on the travel time of military members on BRAC-affected bases.

I also estimate effect of BRAC on the travel time for all commuters (both civilians and military) in BRAC-affected PUMAs in order to quantify the broader impacts of regional growth. In DD-3, my treatment group consists of military and civilian commuters in BRAC-affected regions and my control group consists of military and civilian commuters in adjacent PUMAs (in Figure 2, this group works in the “adjacent” PUMA). Like DD-1, the hope with DD-3 is that choosing reference groups that are geographically adjacent to BRAC-affected PUMAs controls for built environment variables. However, there are certainly a number of important variables that might affect one group but not the other. DD-4 uses a similar control group as DD-2 (the non-BRAC-affected PUMAs) but counts all civilians rather than just the military commuters (in Figure 2, this group is in the “non-BRAC PUMA”).

A DDD-2 model is also estimated in which the control group consists of military and civilian commuters in BRAC-regions and the treatment groups consist of the military and civilians in adjacent PUMAs as well as the military and civilians in non-BRAC-affected PUMAs that have military bases. This model differences out both changes in travel time experienced by individuals in adjacent communities as well as changes in travel time experienced by individuals on non-BRAC affected PUMAs that have military bases. It thus controls for factors that affect both the local area as well as factors affecting all bases, allowing us to identify the effect of the BRAC on the travel time of individuals, both civilian and military, in PUMAs with BRAC-affected bases.

Table 3 below summarizes the six models. Summary statistics of the six DD(D) modes are provided in the Appendix.

**Table 2.3: Descriptions of DD(D) models**

| Model | Population of Interest | Description of Model |
|---|---|---|
| DD-1 | Military only | Treatment group works at BRAC-affected bases and are military. Control group works in same geographic region (i.e. PUMA) as BRAC-affected base but does not work onbase and is civilian. |
| DD-2 | Military only | Treatment group works at BRAC-affected bases. Control group works at unaffected bases and are military members. |

| | | |
|---|---|---|
| DDD-1 | Military only | Treatment group works at BRAC-affected bases. Two control groups are used: civilians who work in same geographic region (i.e. PUMA) as BRAC-affected base and military who work at unaffected bases. |
| DD-3 | Civilians + Military | Treatment groups works in BRAC-affected PUMAs. Control group works at non-BRAC-affected PUMAs that have military bases. |
| DD-4 | Civilians + Military | Treatment groups works in BRAC-affected PUMAs. Control group works at non-BRAC-affected PUMAs that have military bases. |
| DDD-2 | Civilians + Military | Treatment groups works in BRAC-affected PUMAs. Two control groups are used: those who work at non-BRAC-affected PUMAs that have military bases and those who work in adjacent PUMAs. |

The DD models are given by:

$$TT_{irt} = \alpha + \beta_1 post_t + \beta_2 treated_{irt} + \delta post * treated_{irt} + \varphi_r + \theta_t + X_{irt}'\gamma + \varepsilon_{irt} \ , \qquad (1)$$

where $TT_{irt}$ is travel time of individual *i* in PUMA *r* in year *t*; $\alpha$ is a constant, $post_t$ is a dummy variable for post-2005, $treated_{irt}$ is a dummy variable for an active duty military member in DD-1 and DD-2 and for a military or civilian worker in a BRAC-affected PUMA for DD-3 and DD-4, $post * treated_{irt}$ is an interaction variable indicating an individual is in the treated group and in the post period, $\varphi_r$ are state fixed effects, $\theta_t$ are year fixed effects, and *X* is a vector of control variables. I use the following individual-level control variables: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, married, family size, family income, hours worked per week, and number of riders in car. I also use the following land-use control variables: employee density of workplace (workers/sq-km), population density of workplace (people/sq-km), train density of workplace (train workers/sq-km), bus density of workplace (bus workers/sq-km), and a dummy for urban environment. The coefficient of interest is $\delta$, the coefficient on the $post * treated_{irt}$ interaction, as it is the difference-in-difference estimator.

The DDD-1 model is given by:

$$
\begin{aligned}
TT_{irt} = \; & \alpha + \beta_1 post_t + \beta_2 military_{irt} + \beta_3 post * military_{irt} + \beta_4 post * BRAC_{Affected}{}_{irt} \\
& + \beta_5 military * BRAC_{Affected}{}_{irt} + \delta post * military * BRAC_{Affected}{}_{irt} \\
& + \varphi_r + \theta_t + X_{irt}{}'\gamma + \varepsilon_{irt}
\end{aligned} \tag{2}
$$

where $military_{irt}$ are military personnel, $post_t*military_{irt}$ are military personnel after 2005, $post*BRAC\text{-}affected_{irt}$ are military or civilians who live in a BRAC-affected region after 2005, $military*BRAC\text{-}affected_{irt}$ are military personnel in BRAC-affected regions, $post*military*BRAC\text{-}affected_{irt}$ is the interaction term of interest for military personnel who live in the BRAC-affected regions in years after 2005, and other terms are those defined above. The difference-in-difference-in-difference estimator is $\delta$, the coefficient on the $post*military*BRAC\text{-}affected_{irt}$ interaction.

The specification for the DDD-2 model is similar to DDD-1, where instead of $military_{irt}$ I now use all employees in a PUMA with a military base (both BRAC-affected and non-BRAC-affected bases), and instead of $BRAC\text{-}affected_{irt}$ I now use all employed individuals who work in a BRAC-affected PUMA or in a PUMA directly adjacent to a BRAC-affected PUMA. Thus, in DDD-2, the coefficient $\delta$ on the triple interaction term gives the effect of the BRAC on travel time in relation to adjacent PUMAs and other PUMAs with non-BRAC-affected military bases.

Table 4 shows the results for the five DD(D) models, each with two specifications. The interaction term is positive and significant across specifications. Results of the DD(D) estimator $\delta$ show that the employment growth of the 2005 BRAC is associated with 0.26 to 4.89 minutes of additional travel time per commute trip.

**Table 2.4. Results of DD(D) models**

| | Military Only Models | | | | | | Civilians & Military Models | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | DD-1 | | DD-2 | | DDD-1 | | DD-3 | | DD-4 | | DDD-2 | |
| VARIABLES | Drivers Only | Full Model | Drivers Only | Full Model | Drivers Only | Full Model | Drivers Only | Full Model | Drivers Only | Full Model | Drivers Only | Full Model |
| Interaction Effect | 0.63*** | 0.83*** | 4.08*** | 4.9*** | 0.867*** | 0.921*** | 0.617*** | 0.615*** | 3.076*** | 2.894*** | 0.263*** | 0.411*** |
| Std. Error | (0.0738) | (0.0736) | (0.0976) | (0.103) | (0.0868) | (0.088) | (0.0291) | (0.0287) | (0.0576) | (0.203) | (0.0367) | (0.0367) |
| Control Variables‡ | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. (millions) | 3.9 | 4.2 | 0.63 | 0.67 | 12.3 | 13.6 | 9.3 | 9.9 | 0.63 | 0.67 | 26.7 | 29.2 |
| R-squared | 0.589 | 0.566 | 0.636 | 0.599 | 0.56 | 0.539 | 0.567 | 0.541 | 0.636 | 0.599 | 0.544 | 0.513 |

Standard errors in parentheses

Significance codes: *** p<0.001, ** p<0.01, * p<0.05

‡I use the following control variables:

**Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, married, family size, family income, hours worked per week, number of riders in car

**Land-use:** employee density of workplace (workers/sq-km), population density of workplace (people/sq-km), train density of workplace (train workers/sq-km), bus density of workplace (bus workers/sq-km), urban environment

## 2.5 INSTRUMENTAL VARIABLE ESTIMATION

My second approach to estimating the effect of worker density on travel time to work uses the number of gained individuals in the 2005 BRAC as an instrument for worker density. The number of gained individuals in the 2005 BRAC is a good instrument because it is related to worker density but unrelated to travel time to work except through the endogenous variable. This exogeneity was discussed in Section 2. Unlike the DD(D) models, which can only identify the effect of the 2005 BRAC, my IV models identify the effect of worker density on travel time, and therefore has external validity beyond the 2005 BRAC.

The IV model is:

$$TT_{irt} = a + \beta_1 WD_{rt} + \beta_2 TT_{t-1,r} + \beta_3 IX_{irt} + \varphi_r + \theta_t + X_{irt}'\gamma + \varepsilon_{irt} , \qquad (3)$$

where $TT_{irt}$ is travel time to work for individual $i$ in PUMA $r$ at time $t$, $WD_{rt}$ is the worker density of PUMA $r$ at time $t$; $TT_{t-1,r}$ is the average travel time to work in region $r$ in period $t$-1. This variable acts similar to a PUMA-level fixed effect and accounts for variation in travel times between regions. $IX_{irt}$ are interaction terms between the worker density variable and income, age, gender, education, and number of household vehicles per adult household member. These interaction terms only appear in my "Interaction" models. $\varphi_r$ are state-level fixed effects, $\theta_t$ are year fixed effects, $X_{irt}'\gamma$ are the same vector of control variables as in the DD(D) models, and $\varepsilon_{irt}$ is the disturbance term. I instrument for worker density $WD_{rt}$ using the number of gained individuals in the 2005 BRAC. Summary statistics for the data used in the IV models are presented in the Appendix.

Results of eight IV models are shown in Table 5. I run specifications for both military and military plus civilian subgroups. As reported in the table, the first-stage F-statistics are all quite large, and all much larger than 10. The table reports the average effect, which is the coefficient on worker density in the models without interaction terms ("No IX"). In calculating the average effect for the interaction models, I evaluate the interaction terms at the mean value of the household characteristics in each respective interaction. According to my results, worker density has a significant positive effect on travel time to work.

**Table 2.5**: **Results of IV models**

| | *Dependent variable is travel time* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Military Only Models | | | | Civilians + Military Models | | | |
| | All Commuters | | Drivers Only | | All Commuters | | Drivers Only | |
| | No IX | Interaction | No IX | Interaction | No IX | Interaction | No IX | Interaction |
| Average Effect of Worker Density | 0.0070*** | 0.0053*** | 0.00594*** | 0.00324*** | 0.0555*** | 0.05133*** | 0.0494*** | 0.0461*** |
| Std. Error | (0.0005) | (0.1030) | (0.0004) | (0.0291) | (0.0004) | (0.0738) | (0.0004) | (0.1050) |
| Control Variables[‡] | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| First stage F-statistic. | 89.37 | 1387.29 | 63.85 | 799.20 | 10617.36 | 4959.60 | 7575.42 | 89.37 |
| Observations | 278,036 | 278,036 | 265,161 | 265,161 | 3,129,734 | 3,129,734 | 2,935,207 | 2,935,207 |
| R-squared | 0.59 | 0.57 | 0.64 | 0.60 | 0.57 | 0.54 | 0.54 | 0.51 |

Standard errors in parentheses

Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Notes: Worker density is instrumented with the number of gained individuals in the 2005 BRAC. The average effect for interaction terms is estimated using the mean value of the respective interacted variable (e.g. age).

[‡] I use the following control variables:

- **Individual-level**: age, age-squared, education level, income, female, vehicles per capita in household, years in the US, married, family size, family income, hours worked per week, number of riders in car
- **Land-use:** employee density of workplace (workers/sq-km), population density of workplace (people/sq-km), train density of workplace (train workers/sq-km), bus density of workplace (bus workers/sq-km), lives in urban environment

## 2.6 ECONOMIC COSTS OF TRAVEL TIME

Spending additional minutes traveling to work implies an economic opportunity cost. Many suggest that the specific level of service matters when quantifying travel time costs: waiting an additional hour in congested traffic is more costly than waiting an hour in freeflow traffic (Wardman, 1986; Fosgerau et al., 2007). Wardman et al. (2012) use a state choice survey and find that individuals value congested traffic in the UK from 1.18-1.80 times more costly (from light congestion to heavy congestion) compared to freeflow traffic. Others find that the specific mode matters: an hour in a car is less costly than an hour in a crowded bus (Abrantes and Wardman, 2011). Zamparini and Reggiani (2007) conduct a meta-analysis of 90 studies that measure the value of travel time for individuals driving cars. They report that, on average, studies find that travelers value an hour stuck in traffic at 0.82 times their wage rate. Littman (2010) conducts a similar meta-analysis and suggests that when quantifying travel time costs a range of 0.5-1.0 times the individual's wage rate should be used.

I use Littman's method to obtain a back-of-the-envelope estimate of the short-run travel time costs from the 2005 BRAC. From 2006-2010 the average income of military individuals at the BRAC-affected bases was $46,455 per year ($2005) or $17.29/hour using the average number of hours worked per year of 2,686 hrs (Ruggles et al., 2012). Thus, each additional man-hour stuck in traffic congestion results in a cost of $8.65-$17.29 per military commuter. Using the range of coefficients estimated in the DD(D) and IV models, the total cost of the 2005 BRAC to all military commuters is between $1.09-$90.1 million per year ($2005). Applying the same calculations to the non-military workers average wage rate of $24.30 per hour, I estimate the total short-run cost of the 2005 BRAC due to increased commuting time to be $155.1-$1,530.3 million per year ($2005). Results are summarized in Tables 6 and 7 below. The left-hand column uses highest and lowest coefficients of the DD(D) models while the right-hand column uses the highest and lowest coefficients of the IV models. Bolded cells at the bottom provide the range of estimates for each method using 0.5 and 1.0 for wage rate multipliers.

**Table 2.6: Calculations of travel time costs for military members at BRAC-affected bases**

| Military Members | DD Calculations | IV Calculations |
|---|---|---|
| **Data from IPUMS** | | |
| Avg income of military in BRAC-affected PUMAs ($2005) | $46,455 | $46,455 |
| Avg hrs. worked / week by military in BRAC-affected PUMAs (hrs) | 53.23 | 53.23 |
| Avg weeks worked per year by military in BRAC-affected PUMAs (wks) | 50.47 | 50.47 |
| | 2686.63 | 2686.63 |
| **Calculations** | | |
| Hourly Income based on above ($/hr) | $17.29 | $17.29 |
| DD/DDD coefficient on interaction term (avg effect) –low | 0.63 | |
| DD/DDD coefficient on interaction term (avg treatment effect) -- high | 4.90 | |
| IV coefficient on endogenous variables (workers/sq km) – low | | 0.0032 |
| IV coefficient on endogenous variables (workers/sq km) – high | | 0.0051 |
| Total cost of BRAC for all military commuters to BRAC bases ($/day) – Low | $30,225 | $4,301 |
| Total cost of BRAC for all military commuters to BRAC bases ($/day) – High | $356,873 | $294,637 |
| Annual short-run cost of BRAC ($) – Low | **$7,627,207** | **$1,085,303** |
| Annual short-run cost of BRAC ($) – High | **$90,056,177** | **$74,351,219** |

**Table 2.7: Calculations of travel time costs for civilians and military members working in BRAC-affected PUMAs**

| All Workers in BRAC-Affected PUMAs | DD Calculations | IV Calculations |
|---|---|---|
| **Data from IPUMS** | | |
| Avg income of all workers in BRAC-affected PUMAs ($2005) | $46,520.68 | $46,520.68 |
| Avg hrs. worked / week of all workers in BRAC-affected PUMAs (hrs) | 40.52 | 40.52 |
| Avg weeks worked per year of all workers in BRAC-affected PUMAs (wks) | 47.24 | 47.24 |
| **Calculations** | | |
| Hourly income based on above ($/hr) | $24.30 | $24.30 |
| DD/DDD coefficient on interaction term (avg treatment effect) –low | 0.26 | |
| DD/DDD coefficient on interaction term (avg treatment effect) -- high | 0.62 | |
| IV coefficient on endogenous variables (workers/sq km) – low | | 0.0461 |
| IV coefficient on endogenous variables (workers/sq km) – high | | 0.0555 |
| Total cost of BRAC for all commuters to BRAC bases ($/day) – Low | $656,615 | $2,688,319 |
| Total cost of BRAC for all commuters to BRAC bases ($/day) - High | $1,953,829 | $6,478,842 |

| | | |
|---|---|---|
| Annual short-run cost of BRAC ($) – Low | **$155,093,921** | **$634,987,383** |
| Annual short-run cost of BRAC ($) – High | **$461,498,984** | **$1,530,317,643** |

Similar calculations are made for all commuters in BRAC-affected regions and for the US general employed population using the IV coefficients and the estimated US-wide wage rate in Table 8. Use of DD(D) coefficients is not possible for the US-wide effect. One additional employee added per sq km incurs a cost of $0.18-0.44 for all other commuters. While the IV method is often regarded as the "gold standard" in terms of causal models, it says nothing about whether results are externally valid. Thus, these US-wide estimates should be viewed with some degree of caution.

**Table 2.8: Average cost of employment growth for all of US workers**

| Average Effect of Employment Growth | IV Calculations |
|---|---|
| **Data from IPUMS** | |
| Avg income of all US workers ($2005) | $44,855.77 |
| Avg hrs. worked / week (hrs/wk) | 39.94 |
| Avg weeks worked per year (wks) | 46.82 |
| | |
| **Calculations** | |
| Hourly income based on above ($/hr) | $23.99 |
| IV coefficient on endogenous variables (workers/sq km) -- low | 0.0461 |
| IV coefficient on endogenous variables (workers/sq km) -- high | 0.0555 |
| Short-run cost of 10 additional people per sq km ($/commuter/day) -- low | **$0.18** |
| Short-run cost of 10 additional people per sq km ($/commuter/day) -- high | **$0.44** |

It should be noted that Downs (2004) and others express concern about simple travel time value calculations based on wage rate because no two people experience the same cost and some even report a net benefit from added travel time. However, for the purposes of this study, such a calculation provides a convenient quantification of the burden imposed by the BRAC and allows for comparison with other costs and benefits. For example, while the estimates for the total cost of the 2005 BRAC due to increased commuting time were $155.1-$1,530.3 million per year

($2005), the DoD estimated that the 2005 BRAC would provide $37 billion in savings over ten years. A full accounting of the costs of BRAC, however, would include the cost of added travel time as well as other economic costs and benefits associated with the BRAC employment growth.[21]

## 2.7 CONCLUSIONS

When policymakers craft legislation for job growth, they should work with transportation planners to mitigate negative impacts on traffic flow. To some extent, transportation networks are self-regulating (Littman, 2010) and added travelers will eventually find alternative routes, departure times, or modes to compensate for congested networks. While past research has shown that the total employment size of an area is positively correlated with travel time to work, no research has shown the effect of rapid employment growth. Here, results are quite robust – each additional commuter added to the transportation network per square kilometer adds 0.0032-0.055 additional minutes of travel for all other individual commuters.

In terms of short-run economic travel time cost, the 2005 BRAC cost communities near bases between $155 and $1.5 billion per year according to our back-of-the envelope calculation. A full accounting of the economic costs of BRAC should be considered by future BRAC officials and should include travel time costs as well as other costs and benefits not measured here. Lastly, the effect of unanticipated employment growth for the average US commuter is estimated -- an additional commuter per square km will incur a short-run cost of $0.18-0.44 per day for other commuters using the same network.

[21] A full accounting of BRAC would also account for the effects of employment loss on the bases that lost troops. However, when we estimated the DD and DDD models to analyze the effects of losing troops, we were unable to find a robust significant effect of the loss of troops on travel time, suggesting that while employment growth increases travel time, employment loss does not necessarily decrease travel time. We therefore focus on the costs of BRAC to the BRAC-affected regions that gained troops.

A couple specific caveats should be mentioned regarding the data and the conclusions. Freight transportation is affected by increased congestion levels because delays in shipping will inevitably create economic burdens for freight firms, particularly those with perishable products. Due to lack of the necessary freight transport data, this cost is not measured here. Also, considerable heterogeneity exists between cities in their spatial structure, transit availability, transportation policy, natural barriers to travel, and demographic composition. The findings in this study are “average effects” and asymmetric responses between communities are likely. Additionally, adding military members to a community may have a different effect on travel times than adding a similar number of civilian workers. Military commuters have a slightly higher tendency to drive to work and to drive alone (Ruggles et al., 2012). Lastly, some of the increases in travel time measured above could be due to increases in distance of travel, not congestion. However, because the timeframe over which these impacts occurred were on the order of years instead of decades and because of myriad media accounts of increased congestion due to BRAC, the majority of the increases in travel time due to BRAC were likely congestion-related, not distance-related.

## 2.8 REFERENCES


Abrantes, P.A.L., Wardman, M., 2011. Meta-analysis of UK values of time: an update. Transportation Research A 45 (1), 1–17.

Beaulier, S., Hall, J., Lynch, A., 2011. The impact of political factors on military base closures. Journal of Economic Policy Reform 14 (4), 333-342

Cervero, R. 1989. Jobs-Housing Balancing and Regional Mobility. Journal of the American Planning Association 55, no. 2: 139-150.

Cevero, R. 2002. Built environments and mode choice: toward a normative framework. Transportation Research Part D 7, pp. 265-284.

Choo, Sangho, and Patricia L. Mokhtarian. 2008. How do People Respond to Congestion Mitigation Policies? A Multivariate Probit Model of the Individual Consideration of Three Travel-Related Strategy Bundles. Transportation 35:145-63.

De Jong, G., A. Daly, M. Pieters, S. Miller, R. Plasmeijer, F. Hofman. 2007. Uncertainty in traffic forecasts: literature review and new results for the Netherlands. Transportation: 375-395.

Department of Defense. 2005. Report from the Base Closure and Realignment Commission to the President of the United States. Available online at: http://www.brac.gov/finalreport.html. Accessed 15 May, 2013.

Down, A. 1992. Stuck in Traffic. The Brookings Institute, Washington DC.

Downs, A. 2004. Still stuck in traffic. The Brookings Institute, Washington DC.

Duranton, G., Turner, M.A. 2011. The Fundamental Law of Road Congestion: Evidence from US Cities. American Economic Review, 101(6): 2616-52.

Federal Highway Administration (FHWA). 2004. Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation.

Federal Highways Administration. 2007. The Transportation Planning Process: Key Issues. Report from the Federal Transit Administration (FTA).

Federal Highways Administration (FHA). 2010. Status of Nation's Highways, Bridges, and Transit: Conditions and Performance, available at: fhwa.dot.gov/policy/2010cpr/index.htm.

Government Accountability Office (GAO). 2009. Military Base Realignments and Closures: Transportation Impact of Personnel Increases Will be Significant, but Long-Term Costs and Uncertain and Direct Federal Support is Limited. GAO-09-750.

Fosgerau, M., Hjorth, K., Lyk-Jensen, S.V., 2007. The Danish Value of Time Study: Final Report. Danish Transport Research Institute, Knuth-Winterfeldt Allé, Bygning 116 Vest, 2800 Kgs. Lyngby.

Hedgpeth, D. 2005. Businesses to Seek Hints at Base-Closing Hearing. Washington Post. http://www.washingtonpost.com.

Hymel, K. 2009. Does traffic congestion reduce employment growth? Journal of Urban Economics, 65, pp. 127-135.

Kirby, Ron. 2011. Study: Pentagon should pay for transportation improvements necessitated by BRAC. Washington Post. www.washingtonpost.com. Federal Highway Administration (FHWA). 2004. Traffic Congestion and Reliability: Trends and Advanced Strategies for Congestion Mitigation.

Litman, T. 2011. Transportation Cost and Benefit Analysis – Travel Time Costs. Victoria Transport Policy Institute, available online at: www.vtpi.org.

National Academies of Science. 2011. Federal Funding of Transportation Improvements in BRAC Cases: Special Report 302.

New Jersey (NJ). 2005. New Jersey Long-Range Transportation Plan 2030: Statewide Public Opinion Survey, available at: www.state.nj.us/transportation/works/njchoices/pdf/Statewide_Public_Opinion_Survey_Report.pdf

Rodier, C., R. Johnston. 2002. Uncertain socioeconomic projections used in travel demand and emissions models: could plausible errors result in air quality nonconformity? Transportation Research Part A 36, pp. 613-631.

Ruggles, S., J.T. Alexander, K. Genadek, R. Goeken, M.B. Schroeder, and M. Sobek, “Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database],” University of Minnesota, Minnesota, 2010.

Schrank, D. T. Lomax, B. Eisele. 2011. TTIs 2011 Urban Mobility Report. Available online at: http://mobility.tamu.edu/ums/report/.

State of Illinois. “MPO Planning Process: Overview of Transportation Planning Process in Urbanized Areas.”Department of Transportation, State of Illinois. Accessed 12 May, 2012. Available: http://www.dot.state.il.us/opp/MPO%20Process.pdf.

Sweet, Matthias. 2011. Does Traffic Congestion Slow the Economy? Journal of Planning Literature, 26(4), pp. 391-404.

Washington Post. www.washingtonpost.com.

Zamparini, L. and A. Reggiani. 2007. Meta-Analysis and the Value of Travel Time Savings: A Transatlantic Perspective in Passenger Transport. Network Spatial Economics, 7, pp. 377-396.

## APPENDIX FOR ESSAY TWO

### Table 2.A-1: Summary statistics for DD1 groups

| Variable | Obs. | Weighted Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|
| **DD1 - Treatment (Military on BRAC-affected Bases)** | | | | | | |
| Commute Travel Time 2000-05 (min.) | 1,596 | 158,371 | 20.43 | 16.16 | 0 | 183 |
| Commute Travel Time 2006-10 (min.) | 4,497 | 473,431 | 22.52 | 17.32 | 0 | 188 |
| WP Worker Density (workers/sq. km) | 6,093 | 631,802 | 766.12 | 1614.43 | 0.26672 | 24381.7 |
| Age (yrs) | 6,093 | 631802 | 31.18 | 8.05 | 17 | 61 |
| Age Squared ($yrs^2$) | 6,093 | 631802 | 1037.1 | 553.28 | 289 | 3721 |
| Family Inc. ($10,000) | 6,093 | 631802 | 59.92 | 39.92 | 0 | 730.5 |
| Education (yrs) | 6,093 | 631,802 | 7.61 | 1.82 | 0 | 11 |
| Female (0,1) | 6,093 | 631,802 | 0.14 | 0.35 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 6,093 | 631,802 | 1.15 | 0.61 | 0 | 6 |
| Family Size (No.) | 6,093 | 631,802 | 2.9 | 1.49 | 1 | 11 |
| Married (0,1) | 6,093 | 631,802 | 0.71 | 0.45 | 0 | 1 |
| Immigrated to U.S. (0,1) | 6,093 | 631,802 | 0.1 | 0.29 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 6,093 | 631,802 | 53.23 | 14.5 | 0 | 99 |
| Kids in Household (No.) | 6,093 | 631,802 | 1.05 | 1.19 | 0 | 8 |
| Bus Density (bus workers/sq km.) | 6,093 | 631,802 | 0.76 | 2.64 | 0 | 156.47 |
| Train Density (train workers/sq km.) | 6,093 | 631,802 | 0.25 | 0.8 | 0 | 22.05 |
| Urban Household (0,1) | 6,093 | 631,802 | 0.13 | 0.34 | 0 | 1 |
| Rural Household (0,1) | 6,093 | 631,802 | 0.15 | 0.36 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 3,760 | 381,345 | 0.2 | 0.65 | 0 | 33.42 |
| WP Train Density (train wkrs/sq. km) | 3,760 | 381,345 | 0.07 | 0.44 | 0 | 16.52 |
| **DD1 - Control(Civilians in BRAC-affected PUMAs)** | | | | | | |
| Commute Travel Time 2000-05 (min.) | 49,241 | 5,075,661 | 24.99 | 21.95 | 0 | 196 |
| Commute Travel Time 2006-10 (min.) | 134,651 | 14,060,517 | 25.28 | 21.45 | 0 | 200 |
| WP Worker Density (workers/sq. km) | 183,892 | 19,136,178 | 2532.49 | 3534.46 | 0.32 | 194504.9 |
| Age (yrs) | 183,892 | 19,136,178 | 39.24 | 11.81 | 17 | 61 |
| Age Squared ($yrs^2$) | 183,892 | 19,136,178 | 1679.35 | 931.51 | 289 | 3721 |
| Family Inc. ($10,000) | 183,892 | 19,136,178 | 82.77 | 73.98 | -19.99 | 1721 |
| Education (yrs) | 183,892 | 19,136,178 | 7.46 | 2.31 | 0 | 11 |
| Female (0,1) | 183,892 | 19,136,178 | 0.47 | 0.5 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 183,892 | 19,136,178 | 1.23 | 0.71 | 0 | 6 |
| Family Size (No.) | 183,892 | 19,136,178 | 2.95 | 1.6 | 1 | 16 |
| Married (0,1) | 183,892 | 19,136,178 | 0.54 | 0.5 | 0 | 1 |
| Immigrated to U.S. (0,1) | 183,892 | 19,136,178 | 0.18 | 0.39 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 183,892 | 19,136,178 | 40.52 | 11.43 | 1 | 99 |
| Kids in Household (No.) | 183,892 | 19,136,178 | 0.87 | 1.13 | 0 | 9 |
| Bus Density (bus workers/sq km.) | 183,892 | 19,136,178 | 1.55 | 3.12 | 0 | 274.9268 |
| Train Density (train workers/sq km.) | 183,892 | 19,136,178 | 0.55 | 1.09 | 0 | 67.98153 |
| Urban Household (0,1) | 183,892 | 19,136,178 | 0.23 | 0.42 | 0 | 1 |
| Rural Household (0,1) | 183,892 | 19,136,178 | 0.06 | 0.25 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 39,941 | 3,851,335 | 0.11 | 0.39 | 0 | 30.96419 |
| WP Train Density (train wkrs/sq. km) | 39,941 | 3,851,335 | 0.06 | 0.43 | 0 | 55.18086 |

**Table 2.A-2: Summary statistics for DD2 groups**

| Variable | Obs. | Weighted Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|
| **DD2 - Treatment (Military on BRAC-affected bases)** | | | | | | |
| Same as DD1 - Treatment | | | | | | |
| **DD2 - Control (Civilians in BRAC-affected PUMAs)** | | | | | | |
| Commute Travel Time 2000-05 (min.) | 1,546 | 155,681 | 23.50 | 24.67 | 0 | 185 |
| Commute Travel Time 2006-10 (min.) | 4,060 | 424,647 | 22.11 | 20.66 | 0 | 195 |
| WP Worker Density (workers/sq. km) | 7,202 | 738,699 | 1855.92 | 6995.61 | 0.3399474 | 163266.1 |
| Age (yrs) | 7,202 | 738,699 | 30.73 | 7.98 | 17 | 61 |
| Age Squared (yrs$^2$) | 7,202 | 738,699 | 1008.12 | 543.72 | 289 | 3721 |
| Family Inc. ($10,000) | 7,202 | 738,699 | 58.50 | 40.06 | 0 | 730.5 |
| Education (yrs) | 7,202 | 738,699 | 7.53 | 1.78 | 0 | 11 |
| Female (0,1) | 7,202 | 738,699 | 0.13 | 0.34 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 7,202 | 738,699 | 1.14 | 0.63 | 0 | 6 |
| Family Size (No.) | 7,202 | 738,699 | 2.84 | 1.47 | 1 | 11 |
| Married (0,1) | 7,202 | 738,699 | 0.71 | 0.45 | 0 | 1 |
| Immigrated to U.S. (0,1) | 7,202 | 738,699 | 0.10 | 0.29 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 7,202 | 738,699 | 51.71 | 13.88 | 0 | 99 |
| Kids in Household (No.) | 7,202 | 738,699 | 1.00 | 1.17 | 0 | 9 |
| Bus Density (bus workers/sq km.) | 7,202 | 738,699 | 1.26 | 9.28 | 0 | 422.7533 |
| Train Density (train workers/sq km.) | 7,202 | 738,699 | 0.24 | 1.26 | 0 | 52.01862 |
| Urban Household (0,1) | 7,202 | 738,699 | 0.09 | 0.29 | 0 | 1 |
| Rural Household (0,1) | 7,202 | 738,699 | 0.17 | 0.38 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 3,886 | 387,126 | 0.35 | 1.41 | 0 | 62.70433 |
| WP Train Density (train wkrs/sq. km) | 3,886 | 387,126 | 0.18 | 0.73 | 0 | 13.80383 |

**Table 2.A-3: Summary statistics for DD3 groups**

| DD3 - Treatment (All employed individuals in BRAC-affected PUMAs) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs.** | **Weighted Obs.** | **Mean** | **Std. Dev** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 50,837 | 5,234,032 | 24.86 | 21.81 | 0 | 196 |
| Commute Travel Time 2006-10 (min.) | 139,148 | 14,533,948 | 25.19 | 21.34 | 0 | 200 |
| WP Worker Density (workers/sq. km) | 189,985 | 19,767,980 | 2476.03 | 3503.28 | 0.2667204 | 194504.9 |
| Age (yrs) | 189,985 | 19,767,980 | 38.98 | 11.80 | 17 | 61 |
| Age Squared (yrs$^2$) | 189,985 | 19,767,980 | 1658.82 | 928.72 | 289 | 3721 |
| Family Inc. ($10,000) | 189,985 | 19,767,980 | 82.04 | 73.25 | -19.998 | 1721 |
| Education (yrs) | 189,985 | 19,767,980 | 7.47 | 2.29 | 0 | 11 |
| Female (0,1) | 189,985 | 19,767,980 | 0.46 | 0.50 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 189,985 | 19,767,980 | 1.23 | 0.71 | 0 | 6 |
| Family Size (No.) | 189,985 | 19,767,980 | 2.95 | 1.59 | 1 | 16 |
| Married (0,1) | 189,985 | 19,767,980 | 0.55 | 0.50 | 0 | 1 |
| Immigrated to U.S. (0,1) | 189,985 | 19,767,980 | 0.18 | 0.38 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 189,985 | 19,767,980 | 40.92 | 11.75 | 0 | 99 |
| Kids in Household (No.) | 189,985 | 19,767,980 | 0.87 | 1.13 | 0 | 9 |
| Bus Density (bus workers/sq km.) | 189,985 | 19,767,980 | 1.52 | 3.11 | 0 | 274.9268 |
| Train Density (train workers/sq km.) | 189,985 | 19,767,980 | 0.54 | 1.08 | 0 | 67.98153 |
| Urban Household (0,1) | 189,985 | 19,767,980 | 0.23 | 0.42 | 0 | 1 |
| Rural Household (0,1) | 189,985 | 19,767,980 | 0.07 | 0.25 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 43,701 | 4,232,680 | 0.12 | 0.42 | 0 | 33.42399 |
| WP Train Density (train wkrs/sq. km) | 43,701 | 4,232,680 | 0.06 | 0.43 | 0 | 55.18086 |

| DD3 - Control (All employed individuals in adjacent PUMAs) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs.** | **Weighted Obs.** | **Mean** | **Std. Dev** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 33,798 | 3,414,238 | 25.32 | 23.34 | 0 | 197 |
| Commute Travel Time 2006-10 (min.) | 89,601 | 9,191,007 | 25.25 | 22.43 | 0 | 200 |
| WP Worker Density (workers/sq. km) | 123,398 | 12,605,058 | 2790.01 | 4438.69 | 0.6389797 | 87211.6 |
| Age (yrs) | 123,399 | 12,605,245 | 39.42 | 11.89 | 17 | 61 |
| Age Squared (yrs$^2$) | 123,399 | 12,605,245 | 1695.04 | 941.24 | 289 | 3721 |
| Family Inc. ($10,000) | 123,399 | 12,605,245 | 79.82 | 72.22 | -19.998 | 1282 |
| Education (yrs) | 123,399 | 12,605,245 | 7.59 | 2.24 | 0 | 11 |
| Female (0,1) | 123,399 | 12,605,245 | 0.47 | 0.50 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 123,399 | 12,605,245 | 1.25 | 0.72 | 0 | 6 |
| Family Size (No.) | 123,399 | 12,605,245 | 2.73 | 1.51 | 1 | 16 |
| Married (0,1) | 123,399 | 12,605,245 | 0.53 | 0.50 | 0 | 1 |
| Immigrated to U.S. (0,1) | 123,399 | 12,605,245 | 0.12 | 0.32 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 123,399 | 12,605,245 | 40.24 | 11.54 | 1 | 99 |
| Kids in Household (No.) | 123,399 | 12,605,245 | 0.77 | 1.07 | 0 | 9 |
| Bus Density (bus workers/sq km.) | 123,398 | 12,605,058 | 2.43 | 4.26 | 0 | 269.102 |
| Train Density (train workers/sq km.) | 123,398 | 12,605,058 | 0.66 | 1.49 | 0 | 45.13968 |
| Urban Household (0,1) | 123,399 | 12,605,245 | 0.21 | 0.41 | 0 | 1 |
| Rural Household (0,1) | 123,399 | 12,605,245 | 0.19 | 0.40 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 56,807 | 5,658,206 | 0.16 | 0.50 | 0 | 26.93345 |
| WP Train Density (train wkrs/sq. km) | 56,807 | 5,658,206 | 0.12 | 0.45 | 0 | 13.67605 |

**Table 2.A-4: Summary statistics for DD4 groups**

| Variable | Obs. | Weighted Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|
| **DD4 - Treatment (All employed individuals in BRAC-affected PUMAs)** | | | | | | |
| Same as DD3 Treatment | | | | | | |
| **DD4 - Control (All individuals non-BRAC-affected PUMAs with Military Bases)** | | | | | | |
| Commute Travel Time 2000-05 (min.) | 135,665 | 14,112,097 | 26.40 | 23.53 | 0 | 200 |
| Commute Travel Time 2006-10 (min.) | 366,093 | 39,686,549 | 25.83 | 22.03 | 0 | 200 |
| WP Worker Density (workers/sq. km) | 501,757 | 53,798,592 | 13758.7 | 24825.33 | 0.068135 | 545081.7 |
| Age (yrs) | 501,758 | 53,798,646 | 39.06 | 11.79 | 17 | 61 |
| Age Squared (yrs$^2$) | 501,758 | 53,798,646 | 1664.99 | 931.10 | 289 | 3721 |
| Family Inc. ($10,000) | 501,758 | 53,798,646 | 79.35 | 71.56 | -20.1 | 1774 |
| Education (yrs) | 501,758 | 53,798,646 | 7.34 | 2.35 | 0 | 11 |
| Female (0,1) | 501,758 | 53,798,646 | 0.46 | 0.50 | 0 | 1 |
| Veh. Per Adult in Household (No.) | 501,758 | 53,798,646 | 1.15 | 0.76 | 0 | 6 |
| Family Size (No.) | 501,758 | 53,798,646 | 3.02 | 1.76 | 1 | 31 |
| Married (0,1) | 501,758 | 53,798,646 | 0.51 | 0.50 | 0 | 1 |
| Immigrated to U.S. (0,1) | 501,758 | 53,798,646 | 0.29 | 0.45 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 501,758 | 53,798,646 | 40.22 | 11.48 | 0 | 99 |
| Kids in Household (No.) | 501,758 | 53,798,646 | 0.86 | 1.16 | 0 | 9 |
| Bus Density (bus workers/sq km.) | 501,757 | 53,798,592 | 13.00 | 44.88 | 0 | 484.5425 |
| Train Density (train workers/sq km.) | 501,757 | 53,798,592 | 1.25 | 5.30 | 0 | 112.8643 |
| Urban Household (0,1) | 501,758 | 53,798,646 | 0.13 | 0.33 | 0 | 1 |
| Rural Household (0,1) | 501,758 | 53,798,646 | 0.06 | 0.24 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 86,043 | 8,362,252 | 0.49 | 1.51 | 0 | 88.33821 |
| WP Train Density (train wkrs/sq. km) | 86,043 | 8,362,252 | 0.33 | 1.36 | 0 | 48.78015 |

**Note 1: DDD-1 model compares DD-1 treatment with DD-1 and DD-2 comparison groups
**Note 2: DDD-2 model compares DD-3 treatment with DD-3 and DD-4 comparison groups

**Table 2.A-5: Summary statistics for IV-1 models**

| IV-1 (Employed individuals in BRAC-affected PUMAs) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs.** | **Weighted Obs.** | **Mean** | **Std. Dev** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 146,953 | 15,375,148 | 24.50 | 21.28 | 0 | 200 |
| Commute Travel Time 2006-10 (min.) | 146,953 | 15,375,148 | 2488.31 | 3591.86 | 0.27 | 194505 |
| WP Worker Density (workers/sq. km) | 146,953 | 15,375,148 | 26295.61 | 17062.55 | 1600 | 69700 |
| Age (yrs) | 146,953 | 15,375,148 | 23.86 | 4.82 | 9.09 | 58 |
| Age Squared (yrs$^2$) | 146,953 | 15,375,148 | 38.75 | 12.25 | 17 | 62 |
| Family Inc. ($10,000) | 146,953 | 15,375,148 | 1651.83 | 965.65 | 289 | 3844 |
| Education (yrs) | 142,742 | 14,857,231 | 85.35 | 76.17 | -19.998 | 1721 |
| Female (0,1) | 146,953 | 15,375,148 | 7.47 | 2.27 | 0 | 11 |
| Veh. Per Adult in Household (No.) | 146,953 | 15,375,148 | 0.45 | 0.50 | 0 | 1 |
| Family Size (No.) | 142,742 | 14,857,231 | 1.24 | 0.71 | 0 | 6 |
| Married (0,1) | 146,953 | 15,375,148 | 2.87 | 1.61 | 1 | 16 |
| Immigrated to U.S. (0,1) | 146,953 | 15,375,148 | 0.52 | 0.50 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 146,953 | 15,375,148 | 0.18 | 0.39 | 0 | 1 |
| Kids in Household (No.) | 146,953 | 15,375,148 | 41.16 | 12.13 | 1 | 99 |
| Bus Density (bus workers/sq km.) | 146,953 | 15,375,148 | 0.83 | 1.12 | 0 | 9 |
| Train Density (train workers/sq km.) | 146,953 | 15,375,148 | 1.49 | 3.17 | 0 | 275 |
| Urban Household (0,1) | 146,953 | 15,375,148 | 0.51 | 1.07 | 0 | 68 |
| Rural Household (0,1) | 146,953 | 15,375,148 | 0.22 | 0.42 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 146,953 | 15,375,148 | 0.07 | 0.25 | 0 | 1 |
| WP Train Density (train wkrs/sq. km) | 35,002 | 3,445,369 | 0.11 | 0.39 | 0 | 33 |
| Commute Travel Time 2000-05 (min.) | 35,002 | 3,445,369 | 0.05 | 0.36 | 0 | 38 |

**Table 2.A-6: Summary statistics for IV-2 models**

| IV - Drivers (All employed individuals who report driving to work in BRAC-affected PUMAs) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs.** | **Weighted Obs.** | **Mean** | **Std. Dev** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 132,778 | 13,773,195 | 25.66 | 20.19 | 1 | 195 |
| Commute Travel Time 2006-10 (min.) | 132,778 | 13,773,195 | 2456.52 | 3545.45 | 0 | 194505 |
| WP Worker Density (workers/sq. km) | 132,778 | 13,773,195 | 2456.52 | 3545.45 | 0 | 194505 |
| Age (yrs) | 132,778 | 13,773,195 | 26243.72 | 17179.93 | 1600 | 69700 |
| Age Squared (yrs$^2$) | 132,778 | 13,773,195 | 23.95 | 4.83 | 11 | 46 |
| Family Inc. ($10,000) | 132,778 | 13,773,195 | 39.11 | 12.05 | 17 | 62 |
| Education (yrs) | 132,778 | 13,773,195 | 1674.65 | 956.27 | 289 | 3844 |
| Female (0,1) | 131,492 | 13,622,651 | 85.78 | 75.08 | -20 | 1721 |
| Veh. Per Adult in Household (No.) | 132,778 | 13,773,195 | 7.52 | 2.26 | 0 | 11 |
| Family Size (No.) | 132,778 | 13,773,195 | 0.45 | 0.50 | 0 | 1 |
| Married (0,1) | 131,492 | 13,622,651 | 1.26 | 0.70 | 0 | 6 |
| Immigrated to U.S. (0,1) | 132,778 | 13,773,195 | 2.92 | 1.59 | 1 | 16 |
| Hrs. worked per Wk (hrs.) | 132,778 | 13,773,195 | 0.54 | 0.50 | 0 | 1 |
| Kids in Household (No.) | 132,778 | 13,773,195 | 0.18 | 0.38 | 0 | 1 |
| Bus Density (bus workers/sq km.) | 132,778 | 13,773,195 | 41.18 | 11.54 | 1 | 99 |
| Train Density (train workers/sq km.) | 132,778 | 13,773,195 | 0.85 | 1.12 | 0 | 9 |
| Urban Household (0,1) | 132,778 | 13,773,195 | 1.48 | 3.09 | 0 | 275 |
| Rural Household (0,1) | 132,778 | 13,773,195 | 0.51 | 1.07 | 0 | 68 |
| WP Bus Density (bus workers/sq. km) | 132,778 | 13,773,195 | 0.22 | 0.42 | 0 | 1 |
| WP Train Density (train wkrs/sq. km) | 132,778 | 13,773,195 | 0.07 | 0.25 | 0 | 1 |
| Commute Travel Time 2000-05 (min.) | 31,401 | 3,027,274 | 0.11 | 0.37 | 0 | 33 |
| Commute Travel Time 2006-10 (min.) | 31,401 | 3,027,274 | 0.05 | 0.35 | 0 | 38 |

**Table 2.A-7: Summary statistics for IV-3 models**

| IV - Military (Military in BRAC-affected PUMAs) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs.** | **Weighted Obs.** | **Mean** | **Std. Dev** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 4,497 | 473,431 | 22.52 | 17.32 | 0 | 188 |
| Commute Travel Time 2006-10 (min.) | 4,497 | 473,431 | 793.54 | 1650.88 | 0 | 21337 |
| WP Worker Density (workers/sq. km) | 4,497 | 473,431 | 26172.1 | 16281.40 | 1600 | 69700 |
| Age (yrs) | 4,497 | 473,431 | 21.39 | 4.10 | 13 | 41 |
| Age Squared (yrs$^2$) | 4,497 | 473,431 | 31.08 | 8.00 | 17 | 61 |
| Family Inc. ($10,000) | 4,497 | 473,431 | 1030.09 | 544.69 | 289 | 3721 |
| Education (yrs) | 4,497 | 473,431 | 62.52 | 40.39 | 2 | 679 |
| Female (0,1) | 4,497 | 473,431 | 7.58 | 1.81 | 0 | 11 |
| Veh. Per Adult in Household (No.) | 4,497 | 473,431 | 0.14 | 0.35 | 0 | 1 |
| Family Size (No.) | 4,497 | 473,431 | 1.16 | 0.63 | 0 | 6 |
| Married (0,1) | 4,497 | 473,431 | 2.88 | 1.50 | 1 | 11 |
| Immigrated to U.S. (0,1) | 4,497 | 473,431 | 0.70 | 0.46 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 4,497 | 473,431 | 0.09 | 0.29 | 0 | 1 |
| Kids in Household (No.) | 4,497 | 473,431 | 53.47 | 14.25 | 1 | 99 |
| Bus Density (bus workers/sq km.) | 4,497 | 473,431 | 1.04 | 1.20 | 0 | 8 |
| Train Density (train workers/sq km.) | 4,497 | 473,431 | 0.80 | 2.88 | 0 | 156 |
| Urban Household (0,1) | 4,497 | 473,431 | 0.24 | 0.73 | 0 | 15 |
| Rural Household (0,1) | 4,497 | 473,431 | 0.12 | 0.33 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 4,497 | 473,431 | 0.16 | 0.37 | 0 | 1 |
| WP Train Density (train wkrs/sq. km) | 2,709 | 278,036 | 0.15 | 0.64 | 0 | 33 |
| Commute Travel Time 2000-05 (min.) | 2,709 | 278,036 | 0.04 | 0.46 | 0 | 17 |

**Table 2.A-8: Summary statistics for IV-4 models**

| IV - Military, Drivers (Military drivers in BRAC-affected Bases) | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Obs** | **Weight** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| Commute Travel Time 2000-05 (min.) | 4,286 | 450,945 | 22.58 | 16.41 | 1 | 185 |
| Commute Travel Time 2006-10 (min.) | 4,286 | 450,945 | 786.06 | 1624.95 | 2 | 18010 |
| WP Worker Density (workers/sq. km) | 4,286 | 450,945 | 26142.13 | 16109.33 | 1600 | 69700 |
| Age (yrs) | 4,286 | 450,945 | 21.33 | 4.04 | 13 | 40 |
| Age Squared (yrs$^2$) | 4,286 | 450,945 | 31.05 | 7.94 | 17 | 61 |
| Family Inc. ($10,000) | 4,286 | 450,945 | 1027.21 | 541.01 | 289 | 3721 |
| Education (yrs) | 4,286 | 450,945 | 62.16 | 40.22 | 2 | 679 |
| Female (0,1) | 4,286 | 450,945 | 7.59 | 1.81 | 0 | 11 |
| Veh. Per Adult in Household (No.) | 4,286 | 450,945 | 0.14 | 0.35 | 0 | 1 |
| Family Size (No.) | 4,286 | 450,945 | 1.17 | 0.63 | 0 | 6 |
| Married (0,1) | 4,286 | 450,945 | 2.86 | 1.49 | 1 | 11 |
| Immigrated to U.S. (0,1) | 4,286 | 450,945 | 0.70 | 0.46 | 0 | 1 |
| Hrs. worked per Wk (hrs.) | 4,286 | 450,945 | 0.09 | 0.29 | 0 | 1 |
| Kids in Household (No.) | 4,286 | 450,945 | 53.58 | 14.09 | 1 | 99 |
| Bus Density (bus workers/sq km.) | 4,286 | 450,945 | 1.04 | 1.19 | 0 | 8 |
| Train Density (train workers/sq km.) | 4,286 | 450,945 | 0.78 | 2.74 | 0 | 156 |
| Urban Household (0,1) | 4,286 | 450,945 | 0.24 | 0.72 | 0 | 15 |
| Rural Household (0,1) | 4,286 | 450,945 | 0.13 | 0.33 | 0 | 1 |
| WP Bus Density (bus workers/sq. km) | 4,286 | 450,945 | 0.16 | 0.36 | 0 | 1 |
| WP Train Density (train wkrs/sq. km) | 2,582 | 265,161 | 0.15 | 0.64 | 0 | 33 |
| Commute Travel Time 2000-05 (min.) | 2,582 | 265,161 | 0.04 | 0.46 | 0 | 17 |

# ESSAY THREE

Global Dynamic Lifecycle Assessment of Advanced Bioenergy:

Results from an Integrated Assessment Model

## 3.1 INTRODUCTION

As the use of lignocellulosic biomass for fuel expands from less than 10 exajoules (EJ) of primary energy today to – by some estimates – as much as 300 EJ in 2050 (Krey and Clarke, 2011), dramatic shifts may occur in the land use and production of the fuel that alters the fuel's carbon intensity. This study examines these shifts and estimates the resulting greenhouse gas (GHG) intensity of three lignocellulosic bioenergy pathways over the long-term and across mitigation scenarios. Importantly, the study estimates the relationship between a global carbon price and the carbon intensity of these pathways. In particular, we focus on five upstream processes that release GHGs: fertilizer production, $N_2O$ emissions from fertilizer application, biomass harvest, transport, and pre-processing. Although other emissions and processes associated with bioenergy production are important determinants of the net greenhouse gas intensity of a fuel – such as urea, lime, herbicide, and pesticide production; biomass-to-fuel conversion; allocation of co-products, and indirect land-use change – these stages are sufficiently different from the five stages considered here to deserve treatment of their own. The lignocellulosic crops and their respective growing regions modeled in this paper are listed below:

- Miscanthus (Western Europe)
- Switchgrass (all regions but Western Europe/Africa)
- Jatropha (India, Africa)

- Willow (Western Europe, Eastern Europe, China)
- Eucalyptus (Latin America)

A number of changes in global agricultural practices will likely determine the future trajectory of bioenergy's carbon intensity. The fertilizer production process will likely become more efficient and shift towards using more natural gas and less coal and petroleum as an energy feedstock. Energy use and associated emissions from the farming/harvesting step will likely decrease as farming equipment improves and crop yields increase. The biomass transportation stage will likely become more efficient due to improved efficiencies of freight trucking and because the effective supply radius will decrease as average yields increase. However, any movement of bioenergy crops to less productive land will dampen this latter effect. Lastly, biomass to liquid, gas, and electricity conversion efficiencies are expected to continue to improve over time, thus increasing the output of final fuel produced per unit of input primary biomass[22].

Integrated assessment models have been used in the past to examine a number of long-term implications of expanding the bioenergy industry. Wise et al. (2009a) use the Global Change Assessment Model (*GCAM)* to show that pricing emissions from terrestrial carbon sources (above and below ground carbon stock) results in vastly more forest land than an emissions mitigation policy in which terrestrial carbon remains unpriced. Melillo et al. (2011) use the Emissions Prediction and Policy Analysis (*EPPA)* model to demonstrate the important role – particularly after 2050 – that $N_2O$ soil emissions play in bioenergy's net greenhouse gas impacts. Luckow et al. (2010) use the *GCAM* model to show that the availability of carbon

[22] Since the purpose of this study is to estimate changes in carbon intensity over time, no reference fuel is given as is common in fuel LCAs. Here, the reference should be thought of as the first year's (2020) carbon intensity.

capture and storage technology with bioenergy affects where bioenergy is used in the energy system (transportation versus industry). Havlik et al. (2010) use the *GLOBIOM* model to compare the indirect land use impact of first and second generation biofuels, showing that woody biomass from existing forests have the largest potential for GHG reduction of the fuels examined.

This paper consists of four parts. Section two gives background information on the *GCAM* model and my modeling approach to the five upstream stages of bioenergy production considered here: fertilizer manufacturing, fertilizer application, biomass harvest, transport, and pre-processing. Because of their importance and inherent uncertainty, special attention is given to the fertilizer N2O emissions. Additionally, section 2.8 provides details about the nine scenarios used to examine differential effects of carbon policy and energy technology such as carbon capture and storage in the next century. Section three provides three main results and corresponding discussion: (1) the estimated change in carbon intensity over time of the three bioenergy pathways, (2) the effect of yield assumptions and shifts in global land allocation over time, and (3) the trends of the effective supply radius over time. Finally, Section four gives conclusions.

## 3.2 BACKGROUND

### 3.2.1 *GCAM* Background

I use the Global Change Assessment Model (*GCAM*) to analyze climate, energy, agriculture, and land cover for 14 global regions. *GCAM* is a dynamic-recursive partial equilibrium model that solves in five-year time steps to the year 2095. The agriculture and land-use component further subdivides each region into up to 18 agro-ecological zones (AEZs), differentiated based on temperature and precipitation (Monfreda et al. 2009). The intersection of geopolitical regions and AEZs results in 151 agriculture and land use regions (Kyle et al., 2011). Primary bioenergy resources in *GCAM* consist of four streams: (1) traditional biomass[23], (2) conventional bioenergy crops including corn, sugarcane, and oil seed, (3) waste biomass from agriculture, forestry, industrial processes, and municipal solid waste, and (4) lignocellulosic bioenergy crops (Wise et al., 2011; Kyle et al., 2011). The latter is the focus of the present analysis. In the scenarios in this study, lignocellulosic bioenergy crops are introduced in 2020, competing with other land use types based on the relative profitability of bioenergy production in each of GCAM's 151 agricultural regions.

The profitability of lignocellulosic bioenergy supply in *GCAM* is determined by bioenergy crop productivity, the rental rate on land, non-energy costs of crop production, the costs of transformation to fuels, and delivery to consumers. *GCAM* assumes that lignocellulosic crops are transported as a uniform commodity and undergo a pre-processing step to homogenize the biomass stream (Wolf et al., 2006). Others have envisioned similar uniform format systems for the future bioenergy industry (Hess et al., 2009; Richard, 2010). When greenhouse gas emissions are priced, land-use-change $CO_2$ emissions from the conversion of land to bioenergy cropping systems are priced at the same rate as fossil-derived $CO_2$.

Exogenously specified technological growth occurs in all sectors of the economy, including agriculture. Yields are based on FAO (Bruinsma 2009) estimates for 33 agricultural crops in each of 108 countries through 2050, followed by a long-term improvement rate of 0.25% per year in all regions. However, an important note is that the share-weighted average

[23] Use of traditional biomass is expected to decline dramatically in future years (Goldemberg and Coelho, 2004).

yield of bioenergy within a region or for the entire globe may still decrease over time if bioenergy crops expand to less productive land.

### 3.2.2 Modeling Approach for Five Upstream Stages

.

A number of studies and groups have estimated static bioenergy carbon intensities. As an example, Table 1 gives results of several bioenergy pathways examined by the California Air Resources Board (CARB) using the *California-GREET* model. CARB combines the pre-processing stage with the biomass to fuel conversion stage (not shown) meaning the total carbon intensity is low. The cellulosic ethanol pathway has a marked improvement over other bioenergy pathways for nearly every stage of production. Unlike most other crops shown in Table 1, the largest emission source of the five for cellulosic ethanol from poplar is the harvest/farming stage followed closely by the biomass transportation stage, whereas for other crops it’s the $N_2O$ emissions.

**Table 3.1 Carbon intensities ($CO_2$e/MJ) of upstream processes in eight bioenergy pathways.**

| | Cellulosic Ethanol (poplar) (1) | Corn Ethanol Dry-Mill, Midwest Avg (2) | Corn Ethanol Wet Mill, Midwest Avg (3) | Brazilian Sugarcane Ethanol (4) | Sorghum Ethanol (5) | Canola to Biodiesel (6) | Soybean Renewable Biodiesel (7) | Soybean Biodiesel (8) |
|---|---|---|---|---|---|---|---|---|
| Fertilizer Production | 0.32 | 10.30 | 10.70 | 3.70 | 7.47 | 4.70 | 0.58 | 0.61 |
| N2O from Fertilizer | 0.60 | 15.91 | 16.52 | 3.50 | 12.27 | 9.50 | 1.59 | 1.66 |
| Harvest/Farming | 3.34 | 5.56 | 5.81 | 9.90 | 10.78 | 2.08 | 2.08 | 2.17 |
| Biomass Transportation | 2.10 | 2.22 | 2.28 | 2.00 | 2.19 | 0.49 | 1.67 | 1.90 |
| Pre-processing | Na | na | na | na | na | na | na | na |
| Total | 6.36 | 33.99 | 35.31 | 19.10 | 32.71 | 16.78 | 5.92 | 6.34 |

Sources: (1-8) CARB (2013)

3.2.2.1 Fertilizer Production

Fertilizer production is an important source of upstream $CO_2$ emissions for fertilized crops (Wood and Cowie, 2004). One study in the 1990's estimated that fertilizer production accounted for 1.2% of global greenhouse gas emissions (Kongshaug, 1998). Regional differences in $CO_2$

emission intensities arise because of differences in the raw energy input, fertilizer plant design, and plant efficiency (Kahrl et al., 2010; Wood and Cowie, 2004).

Although production of potassium (K) and phosphorous (P) fertilizers contribute to the net emissions of crop production (most analyses put P and K emissions at ~20% of total fertilizer production-related emissions), I limit the focus here to nitrogenous fertilizer production. Using region-specific fertilizer production data from the IEA (2007), I estimate the shares and energy intensity of the different N-fertilizer production technology used in the 14 *GCAM* regions. As shown in Table 2, China relies heavily on coal gasification for its N-fertilizer production (Zhou et al., 2010) while other regions, except for India, primarily use natural gas. As a result, the emission intensity of China-produced fertilizer is much higher than other regions. The coal gasification process is also typically less efficient than the Haber-Bosch process (Rafiqul et al. 2005), which is ,modern natural gas-powered ammonia plants used by most contries. The plant consuming approximately 82% of the natural gas as feedstock and the remaining 18% as fuel (Kongshaug, 1998).

**Table 3.2 Energy and energy intensity for fertilizer production by world region in base year 2005.**

| Region | Fertilizer Production (Mt Ammonia) | Share gas (%) | Share oil (%) | Share coal (%) | Energy Intensity (GJ/t $NH_3$) | Total Fuel Use (PJ/yr) |
|---|---|---|---|---|---|---|
| Africa | 4.0 | 100 | | | 36.0 | 144 |
| Australia_NZ | 1.2 | 100 | | | 36.0 | 43 |
| Canada | 4.4 | 100 | | | 37.9 | 146 |

| | | | | | | |
|---|---|---|---|---|---|---|
| China | 43.7 | 20 | 10 | 70 | 48.8 | 2,133 |
| Eastern Europe | 6.2 | 95 | 5 | | 43.6 | 270 |
| Former Soviet Union | 20.9 | 100 | | | 39.9 | 834 |
| India | 12.2 | 50 | 50 | | 43.3 | 528 |
| Japan | 3.3 | 100 | | | 37.0 | 77 |
| Korea | 2.5 | 100 | | | 37.0 | 100 |
| Latin America | 9.0 | 100 | | | 36.0 | 324 |
| Middle East | 8.5 | 100 | | | 36.0 | 306 |
| Southeast Asia | 7.5 | 100 | | | 37.0 | 315 |
| USA | 10.0 | 100 | | | 37.9 | 400 |
| Western Europe | 12.2 | 90 | 10 | | 35.0 | 427 |
| World | 145.4 | 70.5 | 8.5 | 21 | 41.6 | 6,047 |

Source: IEA (2007)

Fertilizer production emissions can also vary by fertilizer type (e.g. urea versus ammonia). However, Bouwman et al. (2002) demonstrate this is a relatively small effect compared with the overall fertilizer production emissions and is thus ignored here.

*GCAM* is not a trade model and therefore does not track the flow of global fertilizer from producing country to consuming country. Therefore, in this study I estimate the manufacturing-related emissions from fertilizer use in a given region from the characteristics of the fertilizer production sector of that region. Because nearly every region uses natural gas as its primary feedstock except China and to a lesser extent, India, this assumption is only problematic for regions that import large quantities of Chinese-made or India-made fertilizer relative to their total consumption. In 2010, the five largest importers of Chinese fertilizer in terms of weight were India, USA, Bangladesh, Viet Nam, and Malaysia (UN, 2013)[24]. According to the International Fertilizer Association (IFA) (2013), 8% of total fertilizer consumption in India and 6% in the U.S. in 2010 originated in China (UN, 2013; IFA, 2013). Because of the difficulties in forecasting the development of global fertilizer trade over the next century, I make note of the bias created by the importation of Chinese fertilizer but do not attempt to correct it. The mass balance for the 14 *GCAM* regions is shown in Table 3. A detailed description of *GCAM* fertilizer modeling can be found in Kyle (2012).

**Table 3.3 N fertilizer mass balance in each region in 2005 (in Mt N).**

| *GCAM* region | Production | Net exports | Consumption |
|---|---|---|---|
| Africa | 2.99 | 0.13 | 2.86 |
| Australia_NZ | 0.46 | -0.76 | 1.23 |
| Canada | 3.03 | 1.30 | 1.72 |
| China | 29.6 | -0.96 | 30.55 |
| Eastern Europe | 3.98 | 1.27 | 2.71 |
| Former Soviet Union | 10.51 | 8.53 | 1.98 |
| India | 10.49 | -2.25 | 12.74 |

[24] This statistic includes urea and mixtures of urea and ammonium nitrate in aqueous solution (commodity code: 310280).

| | | | |
|---|---|---|---|
| Japan | 0.75 | 0.21 | 0.54 |
| Korea | 0.34 | -0.02 | 0.36 |
| Latin America | 3.10 | -3.07 | 6.17 |
| Middle East | 4.98 | 3.19 | 1.79 |
| Southeast Asia | 6.49 | -2.15 | 8.65 |
| USA | 8.23 | -3.20 | 11.43 |
| Western Europe | 8.28 | -2.23 | 10.51 |
| Global total | 93.23 | 0.00 | 93.23 |

In future periods, the technology choice in the fertilizer production sector is endogenous, and is based on the costs of the different technology options. I assume that China is the only region with a coal-based option for fertilizer production, and in the few regions with oil-based production at present, the technology is phased out by 2035. This assumption is consistent with the trends in India in the last few decades, and with expectations for upcoming decades (Schumaker and Sathaye 1999; Rafiqul 2005). Gas- and coal-based production technologies with carbon capture and storage (CCS) are also modeled, with the additional capital and operating costs of these technologies based on the inputs to the H2A model (DOE Hydrogen and Fuel Cells Program 2013),[25] and the region-specific costs of $CO_2$ transportation, injection, and monitoring from a detailed GIS assessment (Dahowski et al. 2005; 2011; 2013).

In my method of calculating fertilizer production-related emissions using region- and crop-specific fertilizer application rates and region-specific fertilizer manufacturing practices, I focus entirely on synthetic N fertilizer. In reality, some portion will come from organic sources

[25] Hydrogen production accounts for about 80% of all energy use in ammonia production (Schumaker and Sathaye 1999), and it produces a high-purity $CO_2$ stream that would be a prime candidate for $CO_2$ capture systems.

such as manure and crop residues, particularly in developing nations (IPCC, 2006). It is common in jatropha cultivation, for example, to use the jatropha seed husks from one harvest to provide up to 50% of the nitrogen for the next crop cycle (Shinda, 2008). Thus, to the extent that these organic nitrogen sources may account for a substantial portion of bioenergy crop nitrogen requirements, my approach may overestimate the fertilizer production-related emissions required for long-term large-scale bioenergy production. Note that the source of nitrogen—whether organic or inorganic—is thought to be irrelevant for the production of $N_2O$, addressed in the following section (Galloway et al. 2004; Smeets et al 2009).

#### 3.2.2.2 Fertilizer Application

Application of nitrogenous fertilizer to cropland results in the formation of the greenhouse gas, $N_2O$, via nitrification and denitrification processes. $N_2O$ emissions from fertilizer application have been estimated to account for approximately 4% of global greenhouse gas emissions (IPCC, 2011). $N_2O$ emissions from fertilizer are typically categorized into direct and indirect emissions. Direct emissions are those at the field where the crops are grown. Indirect emissions occur elsewhere (e.g. downstream, in groundwater or surface water) and result from N leached from the soil.

In the past, $N_2O$ emissions from fertilizer have been estimated using one of three methods: (1) field experiments which typically measure direct emissions only (e.g. Pedroso et al., 2013), (2) process-based biogeochemical models such as DayCent and DNDC which also measure direct emissions (e.g. Adler et al., 2009), or (3) using the fertilizer application rate and assuming a certain fraction is emitted as $N_2O$. Multi-region analyses usually rely on the latter method, often using the IPCC Tier 1 metholodogy[26]. The IPCC Tier 1 methodology gives the estimated N to $N_2O$ conversion rate for a fertilized plot relative to an unfertilized plot, all else equal.

An alternative approach to the IPCC Tier 1 method has been suggested by Bouwman and Bournan (2002) and Smeets et al. (2009). Using a statistical analysis of a large number of field experiments, they show that the N to $N_2O$ conversion rate can be estimated based on soil texture, soil organic carbon, soil drainage, soil pH, climate type, length of experiment, and frequency of measurements. Stehfest and Bouwman (2006) estimate a similar model for $N_2O$ emissions from natural vegetation and find that vegetation type, soil organic carbon content, soil pH, bulk density and drainage are significant predictors of $N_2O$ emissions from natural vegetation. Both sets of results are used by Smeets et al. (2009) to estimate the global $N_2O$ emissions associated with first generation bioenergy production. In the sections below, a brief background on fertilizer application and yield response is given for each of the five crops considered here followed by a description of the modeling decisions for fertilizer application.

#### 3.2.2.2.1 Switchgrass Fertilizer Application

Due to relatively low nitrogen requirements and relatively high nitrogen uptake efficiency, some have suggested that perennial grasses like switchgrass can be grown without supplemental N fertilizer (Smith et al., 2013). While this may be true for short-term field experiments (Shield et al., 2012), most literature suggests the need for some fertilizer input for

[26] As is the convention, the IPCC distinguishes between direct and indirect emissions. Direct emissions occur at the site of the plant, while indirect occurring later or downstream. The IPCC (2007) Tier 1 methodology recommends using an emission factor of 1.325% for direct emissions plus indirect emissions. Stehfest and Bouwman (2006) use a more disaggregate approach described above and estimate a global average emission factor of 0.91%.

sustained agro-ecosystems (McLaughlin and Kszos, 2003; Schmer et al., 2007; Pedroso et al., 2011).

McLaughlin and Kszos (2003) report results of 13 switchgrass field trials in the U.S. They find that among experimentally tested inputs to switchgrass plants – including nitrogen, potassium, calcium, and phosphorous – only nitrogen had a consistently positive relationship with yield. For long-term switchgrass cultivation, the authors recommend 50 kg $ha^{-1}$ $yr^{-1}$ in Mid-Atlantic states, 41 kg $ha^{-1}$ $yr^{-1}$ in Alabama, and 120 kg $ha^{-1}$ $yr^{-1}$ in Texas where there was a shorter growing season and higher soil temperatures. A substantial yield response to N fertilizer was shown by Lemus et al. (2008) in two field trials in Texas using switchgrass.

Another important consideration is how yield and fertilizer requirements will change over time. Annual yield increases of 1-2% for lowland cultivars of switchgrass and 3-5% for upland cultivars have been observed in switchgrass breeding programs (Taliaferro, 2002). These rates correspond with increases in corn grain yield in the U.S since the early 1900s of 0.7-1.2% (McLaughlin and Kszos, 2003). McLaughlin and Kszos (2003) estimate the maximum theoretical yield of switchgrass by assuming that the maximum yielding individual plant today (6.9 kg) was replicated over an entire hectare. This gives a yield of 47 tons $ha^{-1}$ $yr^{-1}$, or 846 GJ $ha^{-1}$ $yr^{-1}$ assuming an energy density of 18 MJ $kg^{-1}$. Yield increases will also come from new varieties of crops and investments in irrigation systems (Cassman, 1998).

#### 3.2.2.2.2 Miscanthus Fertilizer Application

Miscanthus yields in the literature range from 124 to 564 GJ $ha^{-1}$ $yr^{-1}$ or 7.5 to 34 tons $ha^{-1}$ $yr^{-1}$. Several different optimal fertilizer rate and yield responses have been suggested. In a review of

11 miscanthus field trials, Cadoux et al. (2012) recommend that no fertilizer is applied to miscanthus in its first two years. In subsequent years, the authors recommend 4.9 grams of nitrogen fertilizer per kg of dry plant (equivalent to 82 kg of N-fertilizer $ha^{-1}$ $yr^{-1}$ assuming a yield of 300 GJ $ha^{-1}$ $yr^{-1}$ and an energy density of 16.5 MJ $kg^{-1}$ of dry matter). Miguez et al. (2008) conduct a meta-analysis using non-linear mixed models of miscanthus field trials and also find that miscanthus has a yield response to fertilizer application only after the third growing season.

Other literature suggests that miscanthus yields are maintained across successive years with little or no addition of fertilizer (Sommerville et al., 2010). However, in agrosystems, crops that do not fix N and are harvested annually typically deplete any available N within a few years (Cassman et al. 2002). Davis et al. (2009) report evidence from Illinois, USA that miscanthus fixes nitrogen from the atmosphere allowing it to meet its annual N demand without the use of supplemental nutrients. The authors later state that the ability of miscanthus to fix N likely differs across world regions. Others (Ercoli et al., 1999) have found that irrigation moderates yield response to fertilizer in miscanthus, and that miscanthus is more responsive to inorganic fertilizer than organic fertilizer (Smith and Slater, 2010). Heaton et al. (2008) conduct comparisons of switchgrass and miscanthus grown on identical soils and find that carbon yield and nitrogen uptake efficiency were approximately two times as high for miscanthus than switchgrass. Although there is much excitement about no-fertilizer agrosystems, I feel there are insufficient number of long-term field trials to suggest that no nitrogen will be required in herbaceous energy crops.

#### 3.2.2.2.3 Jatropha Fertilizer Application

Optimal fertilizer practices and yield response have been even less extensively studied in jatropha than switchgrass and miscanthus. Although jatropha was originally grown in Latin America, field trials have only been attempted in parts of India and Africa. Singh et al. (2012) conducted a five-year field trial of jatropha in seven climate and soil conditions in India. Their results suggest that yield and fertilizer requirements are site-specific and that fertilizer has a statistically significant positive influence on jatropha growth. Singh et al. (2012) suggest an optimal fertilizer application of 25 kg N $ha^{-1}$ $yr^{-1}$. Their reported yields (maximum of 1.09 tons $ha^{-1}$ $yr^{-1}$) were far below those assumed in another study, Achten et al. (2008), who assume yield of 1.695 tons $ha^{-1}$ $yr^{-1}$ on degraded land in their lifecycle assessment of jatropha biodiesel in India.

Another study (Sop et al., 2012) reports that on severely degraded land in India, jatropha would require fertilizer in order to survive the first two years. Pandey et al. (2011) state that, because jatropha does not fix nitrogen, long-term cultivation of jatropha requires fertilizer input. The authors also suggest that jatropha typically requires irrigation in arid regions and weed removal, particularly in early years.

#### 3.2.2.2.4 Willow and Eucalyptus Fertilizer Application

The literature is generally in agreement about the robust yield response for woody biomass like eucalyptus and willow to fertilizer (Judd et al., 1996; Smithurst et al., 2003; Heller et al., 2003; Pinkard et al., 2006; Cavenaugh et al., 2011; Stolarski et al., 2011; Forrester et al., 2012; Wang and MacFarland, 2012). The band of optimal fertilization application rates is tighter for willow and eucalyptus than for the three previous energy crops. There is limited evidence that tree crops such as poplar and willow fix nitrogen from the atmosphere which helps minimize inputs (Mitchell, 1995).

### 3.2.2.2.5 Modeling Approach for Fertilizer $N_2O$ Emissions

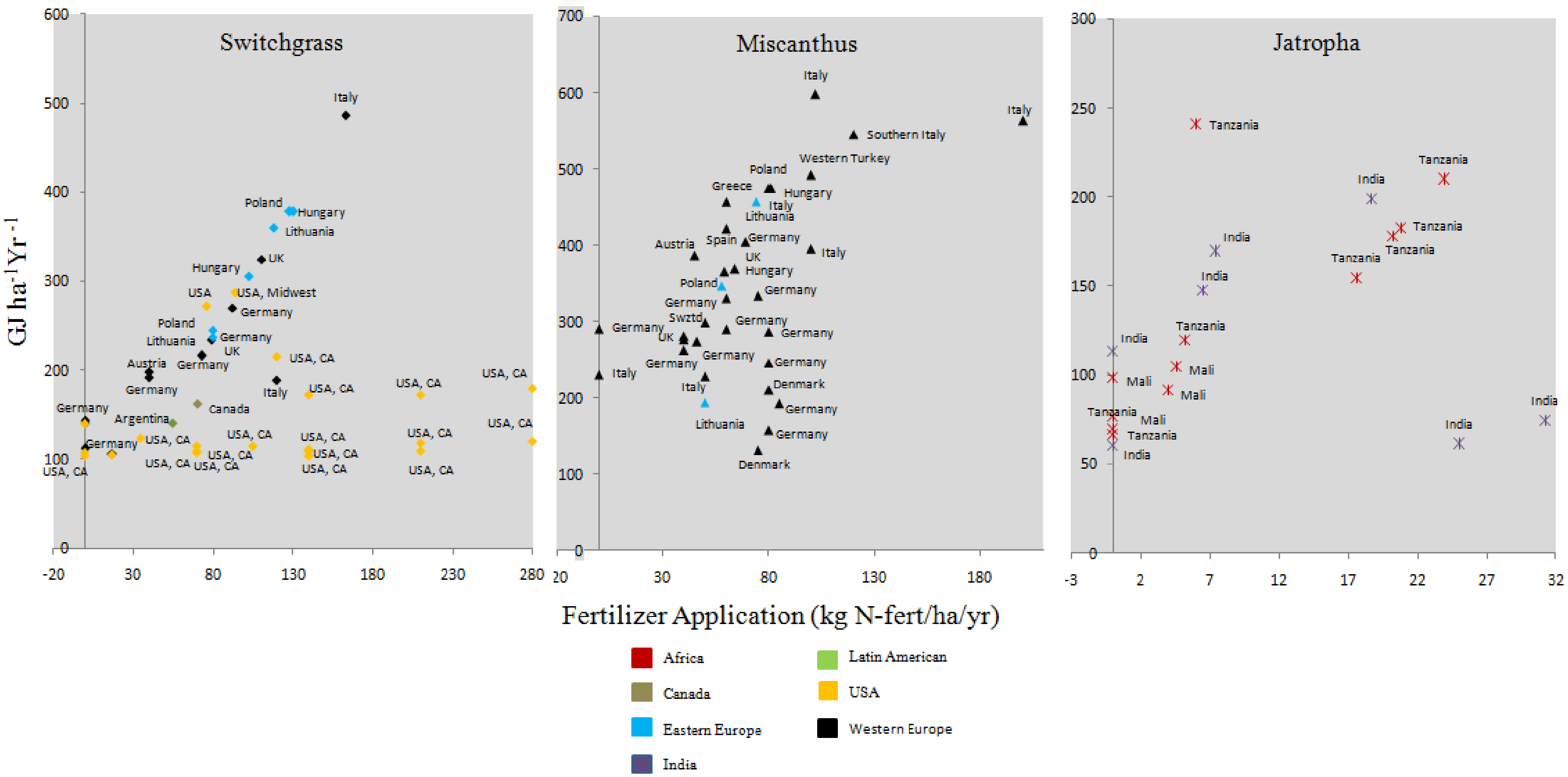
Here, I use the IPCC Tier 1 methodology to model both direct and indirect $N_2O$ emissions[27]. Although the method is relatively straightforward, for a global analysis such as this a number of modeling questions must first be answered, including: (1) how much fertilizer will be applied to bioenergy crops in each world region, in order to be consistent with the assumed yields and economic development pathways of the scenarios? and (2) what is the responsiveness of $N_2O$ emissions to greenhouse gas mitigation policies?

In an economically efficient system, farmers will apply fertilizer until the increase in profits from additional fertilizer application are zero. However, at what point this occurs for different regions of the world and different bioenergy crops in the future is an open question, particularly given that no large-scale lignocellulosic bioenergy production systems currently

[27] Although not used here, the statistical approach towards N2O emission estimation used by Bournan (2002), Stehfest and Bouwman (2006), and Smeets et al. (2009), provides some qualitative conclusions about the N to N2O conversion rate for lignocellulosic bioenergy crops. For example, jatropha is likely to be grown in arid climates with low soil organic matter. According to the regression model in Smeets et al. (2009), such conditions would imply a relatively low N to N2O conversion. As suggested by Achten et al. (2010), the IPCC Tier 1 approach should be seen as an upper bound for jatropha N2O emissions. Similarly, willow grows mostly in northern latitudes which have acidic soil pH and intermediate levels of soil organic matter (Adegibidi et al., 2003). Acidic soils are related to relatively higher emission fractions than basic soils (Stehfast and Bouwman, 2006) therefore we expect, on a global scale, that the IPCC emission fraction would underestimate the emissions from willow. Eucalyptus, switchgrass, and miscanthus are grown on a range of soils and climates. Therefore, the emission fraction associated with these crops should be considered on a more disaggregate basis.

exist. In fact, the literature on jatropha, switchgrass, and miscanthus has considerable variability in both fertilizer application rates and yields. I plot yield and fertilizer application in Figure 2 for a number of field trials in the literature. The figure is meant to be illustrative of the challenges of modeling a global crop system that does not exist today. The figure should be interpreted with caution because yields are determined by a number of factors not shown such as soil type, soil nutrients, climate, and irrigation.

**Figure 3.1 Fertilizer application for several field trials reported in the literature.**
Sources: Melillo et al., 2009; Forrester et al., 2011; UNEP, 2012; Pandey et al. 2011; Singh et al., 2011; Achten et al., 2010; Himken et al, 1997; Boehmel et al. 2008; Ercoli et al., 1999; Smeets et al. 2009; Lewandowski et al. 2000; Vogel et al., 2002; Brejda et al. 1988; Pedroso et al., 2012; Spatari et al. 2005; Groode and Hayward, 2007; Boehmel et al., 2008; Heller et al., 2003; Adegbidi et al., 2003; Ericsson et al., 1994; Ledin, 1986; Willebrand et al., 1993



For my reference case (Ref), I use the share-weighted average fertilizer application rates for all tree crops within a region from a dataset of 88 countries to generate region-specific willow and eucalyptus fertilization rates (FAO, 1999; IFA, 2002). For jatropha, I simply use an application rate of 25 kg N $ha^{-1}$ $yr^{-1}$ for both India and Africa (the two regions which can grow jatropha in *GCAM*) as suggested by Singh et al. (2012). For switchgrass and miscanthus – the most widely available lignocellulosic crops in *GCAM* – I use an optimal value of 60 kg $ha^{-1}$ $yr^{-1}$ for the USA and scale the 13 other regions to the USA based on the historical fertilizer application rates of grass crops (hay, wheat, and barley) from the FAO/IFA dataset (FAO, 1999; IFA, 2002). This scaling is meant to capture differences in farming practices, farmer income levels, soils and climates that lead regions to use different fertilization rates.

For future periods, I hold the fertilizer coefficients constant per unit crop produced; in other words, I assume a linear relationship between yield and fertilizer application rate. This assumption deserves special discussion. The input of fertilizer per unit crop output depends on two factors: the tissue nitrogen content of the crop produced, and the fertilizer recovery efficiency (Cassman et al., 2002). I am unaware of any reason to expect that either of these will change systematically in response to other variables modeled over time. In fact, I have analyzed the available historical data on fertilizer consumption by region, crop, and year from 1971 to 2010, and I do not find evidence for a systematic increase or decrease in the fertilizer input-output coefficient for any of the major grain crops in any of the world regions analyzed.

**Table 3.3.4 Fertilizer application rate in the three scenarios used here (kg N $ha^{-1}$ $yr^{-1}$). Note: ng = not grown in given region.**

| | Willow / Eucalyptus | | | Switchgrass / Miscanthus | | | Jatropha | | |
|---|---|---|---|---|---|---|---|---|---|
| | Ref | Low | High | Ref | Low | High | Ref | Low | High |
| Africa | 50 | 23 | 69 | 38 | 13 | 64 | 25 | 15 | 35 |
| Middle East | 50 | 23 | 69 | 34 | 11 | 57 | ng | ng | ng |
| Eastern Europe | 52 | 24 | 72 | 59 | 20 | 99 | ng | ng | ng |
| Former Soviet Union | 52 | 24 | 72 | 59 | 20 | 99 | ng | ng | ng |
| Western Europe | 68 | 31 | 94 | 83 | 28 | 139 | ng | ng | ng |
| Korea | 68 | 31 | 94 | 98 | 33 | 163 | ng | ng | ng |
| Australia_NZ | 87 | 40 | 120 | 78 | 26 | 130 | ng | ng | ng |
| Canada | 87 | 40 | 120 | 42 | 14 | 70 | ng | ng | ng |
| USA | 87 | 40 | 120 | 60 | 20 | 100 | ng | ng | ng |
| Latin America | 89 | 41 | 124 | 43 | 14 | 72 | ng | ng | ng |
| India | 91 | 42 | 126 | 82 | 27 | 136 | 25 | 15 | 35 |
| Southeast Asia | 91 | 42 | 126 | 65 | 22 | 109 | ng | ng | ng |
| Japan | 145 | 67 | 201 | 98 | 33 | 163 | ng | ng | ng |
| China | 146 | 67 | 202 | 100 | 33 | 166 | ng | ng | ng |

Table 4 shows my base-year (2020) assumptions of fertilizer application rates; note that these rates will increase linearly with assumed yield improvements in subsequent time periods. Because of the importance of this variable in determining the emissions intensity of bioenergy production I construct two additional fertilizer scenarios – High_Fert and Low_Fert – which use application rates of +/-66% the Reference assumptions stated above which represent my best guess of the maximum and minimum average fertilizer application rates for bioenergy crops.

Another modeling challenge arises because the optimal fertilizer application for greenhouse gas mitigation can differ from the optimal application for profit (Kim and Dale, 2008), assuming that fertilizer-related $N_2O$ emissions are not priced. To this point, the main data source for marginal abatement of $N_2O$ as a function of carbon prices is the comprehensive EPA (2006) global mitigation report. However, in this study I do not adopt any such marginal abatement curves, for several reasons. First, these marginal abatement curves did not hold output constant; the decreases in $N_2O$ emissions as a function of carbon prices reflected reduced crop output. Second, it is unclear that agricultural $N_2O$ emissions would actually be included in any emissions mitigation policy, given the difficulty in measuring the emissions, much of which take place far from the site of application and depend on site-specific environmental conditions. Therefore, in these scenarios, the only feedback between carbon prices and $N_2O$ emissions is mediated by the $CO_2$ emissions penalties of fertilizer production, which increase the price of fertilizer, and thereby increase the costs of production in agricultural regions with relatively high fertilizer intensities.

#### 3.3.2.3 Global Biomass Harvest

This stage encompasses all operations associated with the growing and collecting of biomass feedstock. The main energy uses in this stage come from irrigation and tractor energy consumption. Here, a very simple modeling approach is taken: I assume that all five lignocellulosic crops use 0.00746 GJ of diesel fuel $ha^{-1}$ of harvested crop, regardless of the crop type. Therefore, as yields increase over time the energy use $ha^{-1}$ stays the same, but the energy use $GJ^{-1}$ decreases. In this way, I assume that any additional energy requirements from larger harvests are counter-balanced by efficiency improvements in the harvesting equipment. Similarly, in a single time period, higher-yield AEZs consume less energy $GJ^{-1}$ than the lower yield AEZs. Table 5 below gives values of harvest energy reported in the literature. For this paper, I use the GJ total/GJ biomass reported for USA switchgrass of 0.00746.

**Table 3.5 Harvest energy for various bioenergy feedstocks and regions.**

| Region | Feedstock | GJ Electricity/GJ of Biomass | GJ Diesel/GJ Biomass | GJ NG/GJ Biomass | GJ Total/GJ Biomass | Source |
|---|---|---|---|---|---|---|
| USA | Corn | na | na | na | 0.02276 | GREET 2011 |
| USA | Farmed Trees | na | na | na | 0.01415 | GREET 2011 |
| USA | Switchgrass | na | na | na | 0.00746 | GREET 2011 |
| USA | Corn Stover | na | na | na | 0.01136 | GREET 2011 |
| USA | Forest Residue | na | na | na | 0.01387 | GREET 2011 |
| USA | Forest Residue | 0.00528 | 0.03840 | na | 0.04368 | CARB, 2011 |
| USA | Sorghum | 0.03585 | 0.00005 | 0.02865 | 0.06456 | CARB, 2010 |
| Latin America | Sugar Cane | na | na | na | 0.00573 | GREET 2011 |
| Western Europe | All | na | na | na | 0.00076 | IRENA IFS 11 |
| Western Europe | Poplar | na | na | na | 0.04512 | Fantozzi & Buratti 2010 |
| Canada | Selection cut | na | na | na | 0.01530 | Zhang et al. 2010 - Supp info |
| Canada | Shelterwood cut | na | na | na | 0.02106 | Zhang et al. 2010 - Supp info |
| Canada | Clear cut | na | na | na | 0.01813 | Zhang et al. 2010 - Supp info |
| Average | | 0.02057 | 0.01923 | 0.02865 | 0.02184 | |

The assumption of constant harvest energy per hectare is supported in historical data; between 1961 and 2005, the number of tractors per thousand metric tonnes of agricultural output (proportational to a GJ of biomass) remained relatively constant at 6.4 to 5.9, respectively (IFA, 2012). At the same time, tractor efficiency has changed very little (Grisso et al., 2010)[28]. Ultimately, because harvest energy and emissions represent such a small portion of total GHG emissions from biocrop cultivation, any assumption on harvest energy will have a relatively small impact on the long-term dynamics of carbon intensity.

### 3.2.4 Global Biomass Transport

The supply radius of the bioenergy agrosystem is a main factor in determining the energy use in biomass transport. Because the size of bioenergy conversion facilities in a vastly expanded bioenergy world is uncertain, I simply assume that all biorefineries and bioelectricity plants will

[28] The authors show that the average available fuel economy of tractors in the U.S. increased from 14.5 horsepower-hours gallon-1 (hp-h/gal) in 1980 to 16.5 hp-h/gal in 2000. The trend in efficiency gains will obviously differ by world region and by type of agriculture, soil, and climate. However, in general the trend in tractor efficiency is very slowly upwards.

be sized accept 2.0 million tons of feedstock per year (roughly the quantity needed for a 200 million gal $yr^{-1}$ biorefinery) and that the supply radii will change as yield changes (i.e. as yield increases, the effective supply radius for a single biorefinery shrinks and the corresponding energy use $GJ^{-1}$ decreases). Additionally, I assume that the fraction of land within the supply radius which is growing biocrops stays constant at 60% and that the Tortousity factor (a measure of how indirect the roadway is within the supply radius) is 1.5 in accordance with Wright and Brown (2007). Lastly, I assume that the fuel economy of freight trucks in developed and developing countries is 0.84 MJ ton-$km^{-1}$ and 1.80 MJ ton-$km^{-1}$, respectively[29].

Given this set of assumptions as well as the exogenous assumptions about yield, the supply radii decrease from 38.4-141.3 km in 2005 and 29.7 km-106.8 km in 2095[30]. On average, the supply radii decrease by 25% in this time.

### 3.2.5 Global Biomass Pre-processing

The pre-processing stage includes the unloading, queuing, and handling of biomass and all processes that physically transform the feedstock into the format required by the biorefinery such as drying, grinding, and pelletization, and/or torrefaction.

Most research that examines future bioenergy supply chains recommends adoption of a multiple-stage pre-processing system (Hess, 2008; Uslu et al., 2008; Richard, 2010). The first stage could be a small densification unit near the growing field which serves to reduce the

[29]Both numbers are from the GREET model (2011). Developing countries corresponds to fuel economy of medium duty vehicles and developed countries to heavy duty vehicles. Developed countries, on average, use smaller freight vehicles than developed countries.

[30] In both cases the shortest supply radius is for miscanthus in Western Europe and the longest for eucalyptus in Africa.

biomass transportation costs. The second stage could be at the biorefinery (or elsewhere) and would serve to prepare the biomass for conversion to fuel.

In *GCAM*, this pre-processing stage is accounted for using a cost adder to the non-energy cost of bioenergy. Additionally, for this study, I modify *GCAM* to account for energy use in the pre-processing stage. Table 6 below gives literature values for the pelletization energy for several world regions and feedstocks. As is apparent, most values from the literature are for pelletization of wood biomass. These pellets are used largely in Europe and increasingly in the U.S. in home pellet stoves. Since a largescale lignocellulosic bioenergy industry does not exist, only three sources were found that report pelletization energy use for non-wood biomass. Because wood biomass has very high moisture content relative to other feedstock (up to 50% compared to ~15% for field-dried switchgrass), the high energy consumption for wood shown in Table 6 goes for drying the biomass. To avoid overestimating energy use in the pre-processing stage, I use the coefficient for switchgrass from Samson et al. 2001 for all purpose-grown bioenergy feedstock streams. I feel the pre-processing stage in general deserves more attention in future studies.

**Table 3.6 Pelletization energy requirements for selected crops and regions.**

| Region | Feedstock | GJ Biomass/GJ Biomass Pellets | GJ Electricity/GJ of Biomass Pellets | GJ Diesel*/GJ Biomass Pellets | GJ NG/GJ Biomass Pellets | Total Energy (GJ/GJ Pellets) | Size of Plant (GJ Pellets/year) | Source |
|---|---|---|---|---|---|---|---|---|
| Europe | Wood | 0.01000 | 0.01292 | 0.02184 | 0.00015 | 0.04491 | 153,300 | Fanozzi and Buratti 2010 |
| Europe | Wood | 0.20983 | 0.03160 | na | na | 0.24142 | 390,915 | Thek & Obernberger, 2002 |
| Europe | Wood | 0.10368 | 0.02833 | na | na | 0.13201 | 1,303,050 | Thek & Obernberger, 2002 |
| Latin America | Wood | na | na | na | na | 0.03159 | 1,072,215 | Uslu et al. 2008 |
| Latin America | Wood | 0.19429 | 0.03578 | 0.01042 | na | 0.24048 | 413,910 | Uasuf and Becker, 2011 |
| Latin America | Wood | 0.09714 | 0.03408 | 0.01042 | na | 0.14163 | 413,910 | Uasuf and Becker, 2011 |
| Latin America | Wood | 0.19429 | 0.03206 | 0.06944 | na | 0.29579 | 827,820 | Uasuf and Becker, 2011 |
| Latin America | Wood | 0.09714 | 0.02909 | 0.00694 | na | 0.13318 | 827,820 | Uasuf and Becker, 2011 |
| Canada | Wood | 0.21429 | 0.03086 | 0.00000 | 0.00260 | 0.24774 | 2,310,000 | Bradley 2004 |
| Canada | Wood | 0.18103 | 0.02309 | 0.01177 | 0.00000 | 0.21589 | 921,053 | Magelli 2009 |
| Canada | Wood | 0.18000 | 0.02957 | 0.03209 | 0.00000 | 0.24166 | 919,800 | Zhang et al. 2010 (supp info), |
| Canada | Wood | na | na | na | na | 0.14208 | 290,000 | Kabir & Kumar, 2012 |
| Canada | Wood | na | na | na | na | 0.17008 | 290,000 | Kabir & Kumar, 2012 |
| Canada | Ag waste | na | na | na | na | 0.02144 | 150,000 | Kabir & Kumar, 2012 |
| Canada | Switchgrass | na | na | na | na | 0.02377 | 14,892 | Natural Resources Canada, 2( |
| Canada | Switchgrass | na | na | na | na | 0.02743 | 1,159,715 | Samson et al. |
| Average | | 0.14817 | 0.02874 | 0.02036 | 0.00069 | 0.16428 | 734,557 | |

### 3.2.6 Co-Products

Unlike many first generation energy crops, second generation crops produce very few co-products. Electricity will likely be the most significant co-produce for these purpose grown crops, with the exception of jatropha which produces seed cake, wood, and shells as co-products (Wang et al., 2011; IPCC, 2011) and eucalyptus and willow which yield tree bark. Thus this study does not explicitly consider co-products in bioenergy production, except electricity that are implicitly wrapped into the input-output coefficients of biomass to fuel conversion.

### 3.2.7 Calculations of Carbon Intensity

Section 2 of the SI gives a description of the calculations used for estimating the greenhouse gas intensity of bioliquids, biogas, and bioelectricity. I categorize the five upstream stages by five emission streams: $N_2O$ from fertilizer, and $CO_2$ from fertilizer production, harvest, transport, and pre-processing. Variables are defined as either exogenous (determined outside the model) or endogenous (determined within the model). The main endogenous variables are the quantities of feedstock produced in each of the 151 AEZs each year and the quantities of fuel produced in the producing regions. By aggregating quantities of primary or final energy, share-weighted global values are estimated.

In this study, I estimate emissions per unit of final energy, not primary energy. Thus, an important determinant of GHG intensity is the efficiency with which the primary energy delivered to the biorefinery is converted to final energy. For bioliquids, this entails conversion from biomass to liquids in a biorefinery and pipeline delivery to service stations. For bioelectricity, this means biomass to electricity conversion followed by transmission along an electrical grid to the end use device. Finally, for biogas, this entails biomass to gas processing followed by pipeline delivery to the end user. These efficiencies are documented in the GCAM Wiki (2013). Each of the three conversions has a different assumed efficiency over time, meaning a differential effect on the carbon intensity.

### 3.2.8 Scenarios

A set of 13 scenarios are used to identify key relationships between carbon policy and bioenergy carbon intensity.

- Baseline scenario (*Base*) – technology advancement follows historical trends. No carbon policy is adopted in this scenario and therefore there is no price signal to incentivize market penetration of low-carbon technologies or more efficient technologies beyond normal cost considerations by energy suppliers and consumers. Carbon capture and storage (CCS) does not become available.
- Carbon tax scenarios (e.g. *CTax_5*) – Technology advancement follows historical trends. Carbon taxes are adopted to provide a price signal to incentivize market penetration of low-carbon technologies or more efficient technologies beyond normal cost considerations by energy suppliers and consumers. Carbon taxes begin in the year 2020 at \$5, \$10, \$20, and \$25 tonne$^{-1}$ and increase at a Hotelling schedule of 5% per year to 2095. Abbreviations are *CTax_5, CTax_10, CTax_15*, *CTax_20*, and *CTax_25*, respectively. I run five scenarios with CCS (e.g. *CTax_5_CCS*) and five scenarios

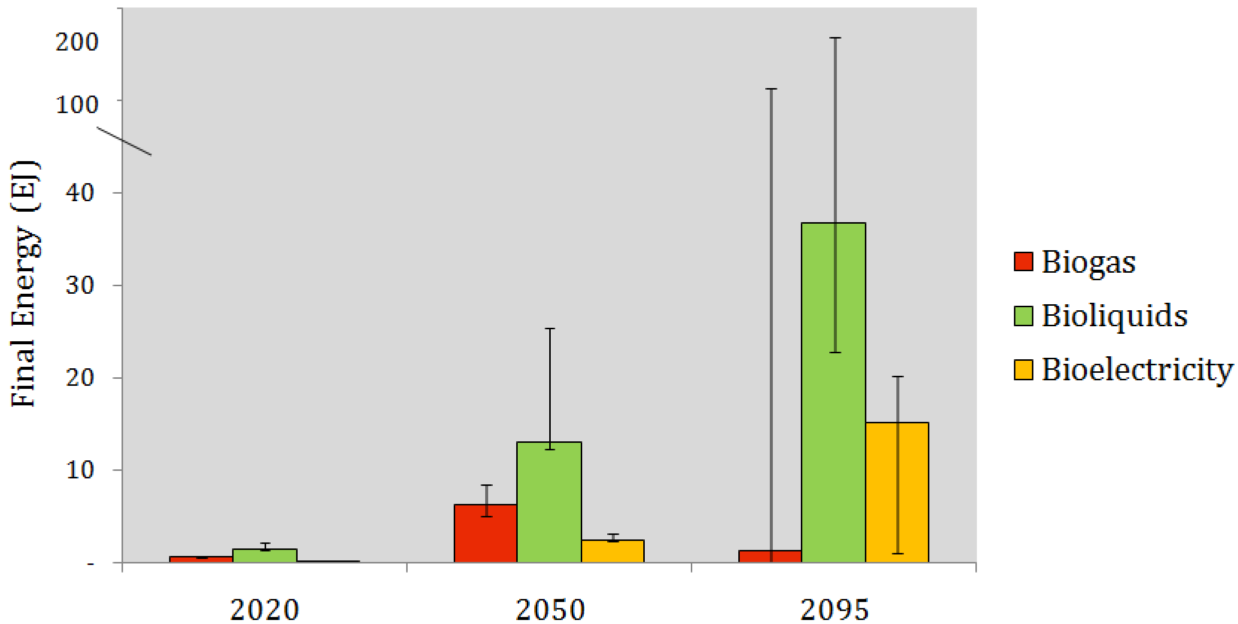
without CCS (e.g. *CTax_5_noCCS*). Lastly, given the important role of CCS technologies determining the contribution of bioenergy and other renewable and nuclear resources, I run five additional scenario in which changes in terrestrial carbon stock (above and below ground) are also taxed (*CTax_25_Terrestrial*).

- Fertilizer scenarios (e.g. *High_Fert*) – I include two fertilizer scenarios based on uncertainty bounds for two parameters: 1) fertilizer application and 2) Nitrogen-to-N2O conversion rate. *High_fert* accounts for high fertilizer application and high N-N2O conversion rate, while *Low_fert* is low fertilizer application and low N-N2O conversion rate.

Tables S.1 of the supplementary material summarize the scenarios adopted in this study including corresponding $CO_2$ concentration, estimated median temperature rise, and carbon prices. Given the array of fertilizer application rates that could be used to characterize an expanded global bioenergy crop system, I develop three fertilizer-$N_2O$ scenarios: (1) a reference fertilization scenario used in the base scenario and all carbon policy scenarios, (2) a high input scenario (High Fert), and (3) a low input scenario (Low Fert).

Figure 2 shows the range of lignocellulosic crops across scenarios for 2020, 2050, and 2095. Error bars represent the range, columns represent the median values. Bioliquids is generally the dominant use of lignocellulosic biomass across scenarios. The maximum quantity of final energy from purpose-grown bioeerngy crops is in the Ctax_25_Terrestrial scenario which has a total of 406 EJ of final energy or 761 EJ of primary energy (biogas 165 EJ, bioliquids 527 EJ, bioelectricity 68 EJ).

**Figure 3.2 Final energy use across scenarios for 2020, 2050, and 2095 (EJ). Columns are the median values. Error bars represent the range across scenarios.**

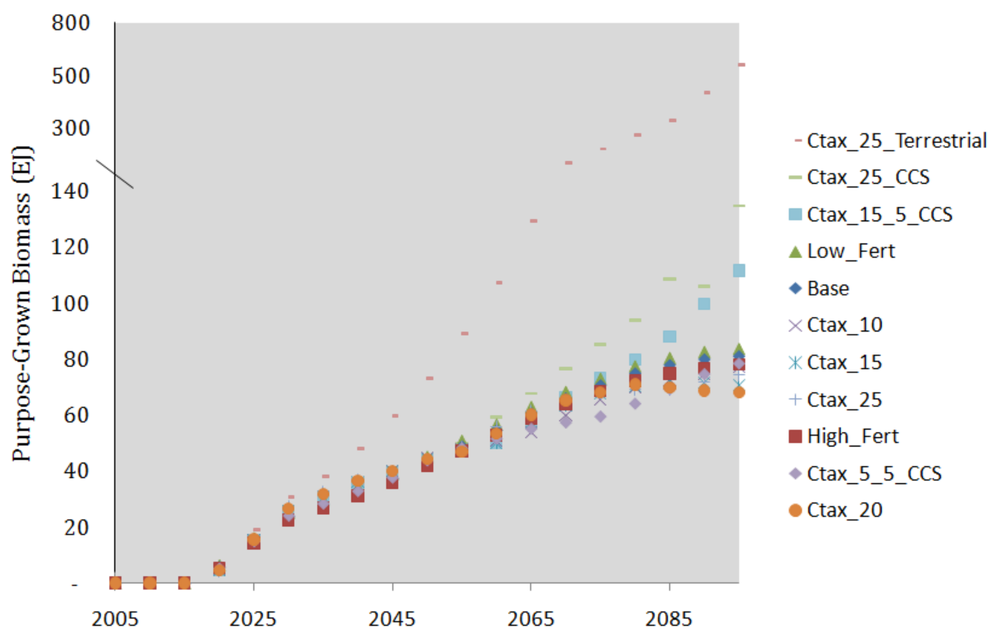



In CCS scenarios I observe greater quantities of bioelectricity and bioliquids (the two CCS paths) and less biogas than the same scenario without CCS. This fits with Luckow et al.'s (2010) results.

3.2.9 Biomass production in each scenario

Figure 3 shows the total primary biomass production in each scenario. Most scenarios have very similar trajectories with the exception of when CCS is available and when terrestrial carbon is not priced. With CCS, bioenergy becomes more attractive than without CCS because of the ability for a low carbon energy resource along with negative $CO_2$e emissions. Not pricing terrestrial carbon results in large-scale deforestation for bioenergy production, releasing a large amount of $CO_2$ from land-use-change (Wise et al., 2009).

**Figure 3.3 Primary EJ of purpose-grown bioenergy by scenario. Figure demonstrates that not taxing terrestrial carbon sources leads to the largest production followed by CCS scenarios.**




3.2.10 Exogenous yield assumptions

As stated in the main text, each scenario uses the same exogenously-specified assumptions about bioenergy crop yields. These generally follow the median of all crops for the given region and crop, which are based on FAO projections of yield to 2050, with an assumed increase of 0.25%

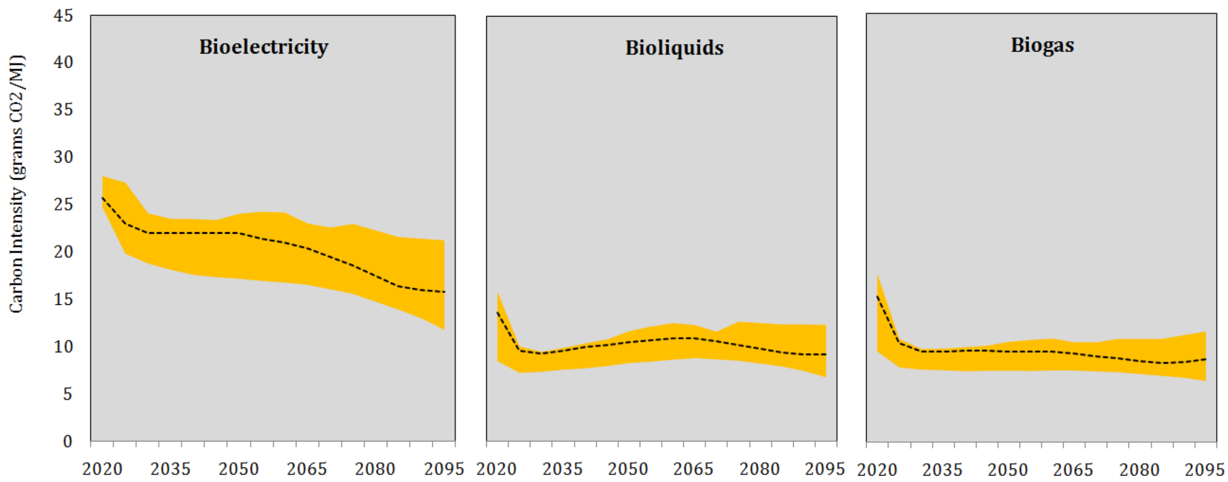
per year thereafter (Table S2 of the Supplementary Information). Yield assumptions have a direct effect on two of the five upstream stages considered here: the harvest energy (for a given region-year-AEZ, higher yield implies less harvest energy per $GJ^{-1}$ biomass produced), and the biomass transportation energy (for a given region-year-AEZ, higher yield implies less transportation energy $GJ^{-1}$ transported).

## 3.3. RESULTS

### 3.3.1 Main results

Figures 4A-C give the range of whole-system emission intensity for the carbon tax, reference, and CCS scenarios. These emissions include all modeled inputs to the bioenergy production processes, traced back to primary energy, plus the N2O emissions, converted to CO2e using the hundred-year global warming potential in the Second Assessment Report (IPCC 1996). Perhaps the most surprising fact is that, with the exception of early years, the carbon intensity trends are relatively flat, despite increasing technology and yield assumptions in all scenarios. Biogas and bioliquids coefficients are both smaller in magnitude and have a smaller band than bioelectricity. Bioelectricity has the highest average emission intensity, due in large part because of the poor base-year efficiency of biomass to electricity conversion. Note that as the older biomass power plants are retired over time, the emissions intensity of this pathway improves.

**Fig 3.3A-C. Overall results showing carbon intensity ($CO_2$ e $MJ^{-1}$ final) of all scenarios except High_Fert and Low_Fert scenarios. Only the max, min (yellow band), and median (black dotted line) scenarios are shown. Other scenarios fall within the range shown.**

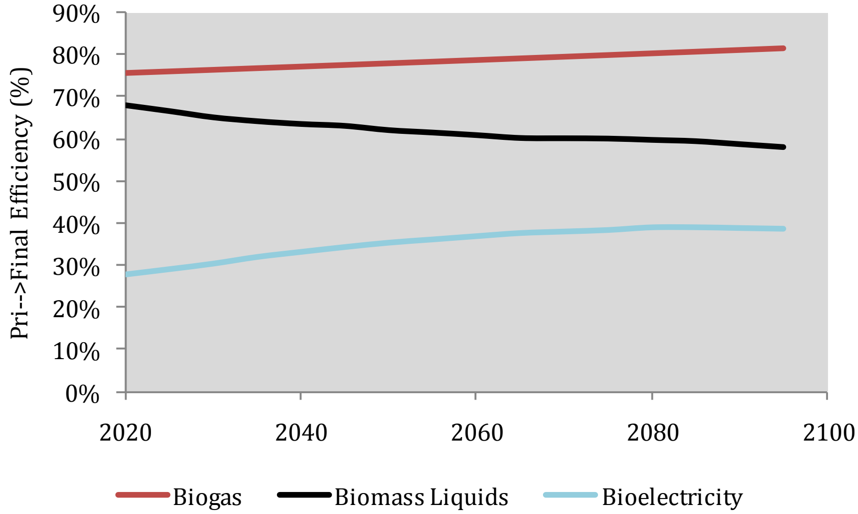



The median line for bioelectricity drops by about 50% between 2020 and 2095, whereas bioliquids and biogas decline by 25-27%. The progression of carbon intensities in figure 3A-C is actually a combination of several moving variables discussed below.

### 3.3.2 Efficiency changes over time

This study does not focus on the efficiency of converting pre-processed biomass to final fuels, as GCAM already has detailed representations of these processes. However, since my carbon intensity metric is in units of final energy (liquid, gas, or electricity delivered to the end user), this efficiency plays an important role in the trajectory of the carbon intensity values, and is shown at the global level in Figure 4. The higher the primary to final efficiency, the fewer MJ of primary input energy needed for the same quantity of final energy; thus, the lower the carbon intensity value. For example, this means that the seven percentage point increase in bioelectricity will contribute to

**Fig. 3.4. Global share-weighted primary to end-use efficiency trends for biogas, bioliquids, and bioelectricity**

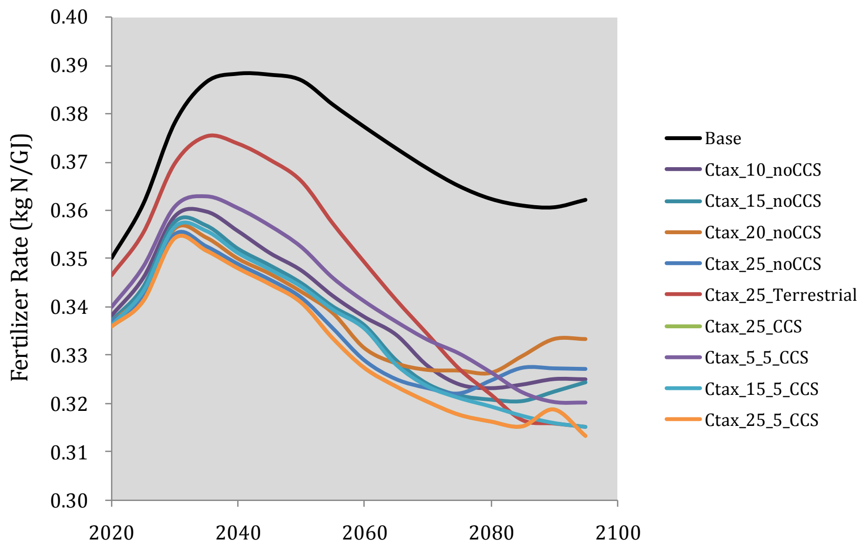



Bioelectricity changes by the largest magnitude in percentage points and the largest overall percentage between 2020 and 2095. This contributes to bioelectricity's declining carbon intensity trend in Fig. 3A.

3.3.3 $N_2O$ Emission Trends

$N_2O$ emissions contribute very little to changes over time in Fig. 3A-C because of the assumption of constant fertilizer application per GJ of primary biomass, and because I have not adopted a marginal abatement curve for these emissions. The only factor which shifts the $N_2O$ emission intensity over time is the allocation of bioenergy to different regions with different fertilizer application rates. In other words, the "effective fertilizer rate" may change with shifting biocrop cultivation between regions. Figure 5 demonstrates how as bioenegy crops expand globally biocrops to move towards higher fertilizer regions before 2050 and towards lower fertilizer regions after 2050.

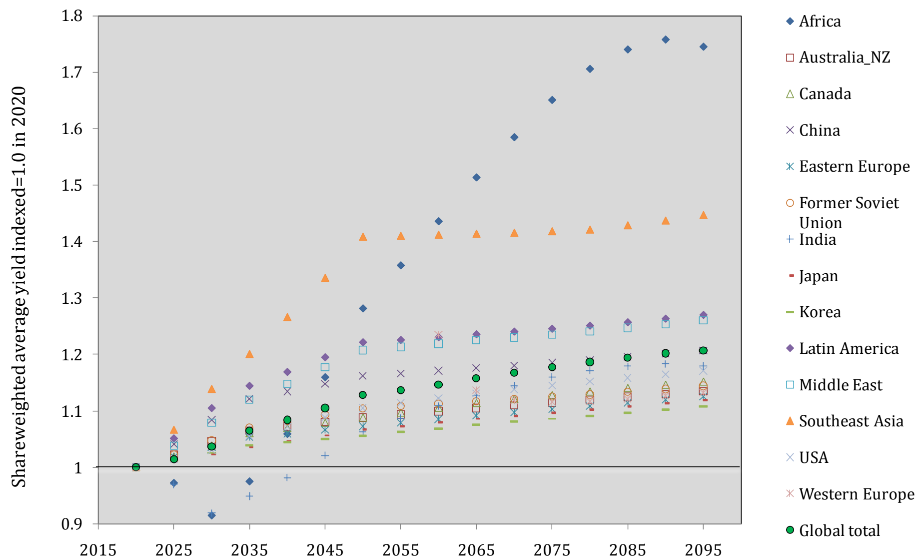
**Figure 3.5 Changes in average fertilizer rate over time, across scenarios. Figure clearly demonstrates how – given constant fertilizer application assumptions – the "effective" fertilizer rate can still vary over time because of shifting land use patterns.**




3.3.4 Global shifts in growing regions

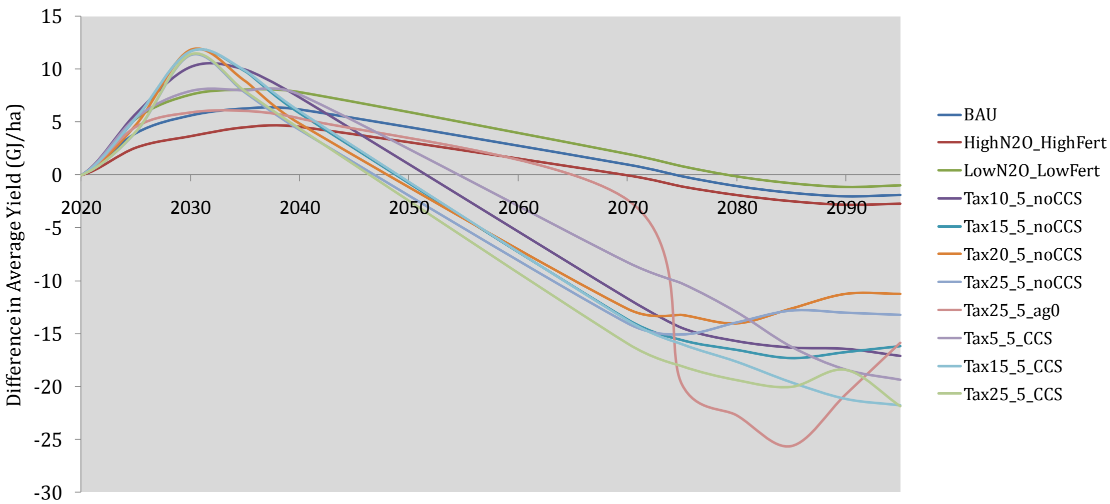
As discussed above, the average yield of biocrops directly impacts the fertilizer emissions (higher yield in a given AEZ from one year to the next implies lower fertilizer input per unit of energy) and the transportation emissions (higher yields lead to smaller supply radii and less energy use) from bioenergy. In this section, I examine inter-regional shifting in bioenergy crop production over time and between scenarios. To start, I plot the average bioenergy yield by region in Figure 6. Each AEZ has been weighted by its cumulative bioenergy production. The figure reflects two general trends: (1) increasing yields across all AEZs according to exogenously specified yield improvements and (2) movement of shares of bioenergy crops between AEZs (endogenously determined). With a few exceptions, most regions follow similar trajectories, getting 10%-20% higher yield from 2020 to 2100. Africa has the greatest increase in effective yield while Korea has the lowest. At a global scale, the effective yield of bioenergy crops increases by 21% between 2020 and 2100.

**Figure 3.6 Effective yield in BAU case (indexed to 1.0 in 2020). Figure demonstrates how despite the exogenous and uniform yield improvements in GCAM, range differ in how they change over time. The effective yield in Africa for biocrops increases by ~70% between 2020 and 2095 whereas in Korea, the increase is less than 10%.**




In order to quantify the shifting of biocrop cultivation between AEZs of different yields in these scenarios, next I hold the land allocation in the year 2020 constant, but allow yields to increase within each AEZ. I then compared the effective yield in this "no movement" case to the effective yield in the GCAM output for each of the 13 scenarios. Figure 7 gives the difference between the "no movement" and "movement" cases (a positive value indicates that the effective yield is less than the case in which no movement of crop shares is occurring). Across scenarios, biocrops move towards less productive land before 2050 and towards more productive land after 2050, relative to the no movement case.

**Figure 3.7 Effective yield at the global level and across scenarios.**




3.3.3.5 Shifts in Supply Radius

As discussed above, average supply radius of AEZs that produce bioenery declines by about 25% between 2005 and 2095 across scenarios, contributing to decreases in energy use and emissions from the transportation stage. However, because of the shift in bioenergy crops towards less productive land *than would be achieved without movement of crops*, this improvement is dampened.

**Figure 3.8. Average supply radius decline across scenarios from 2005 to 2095.**

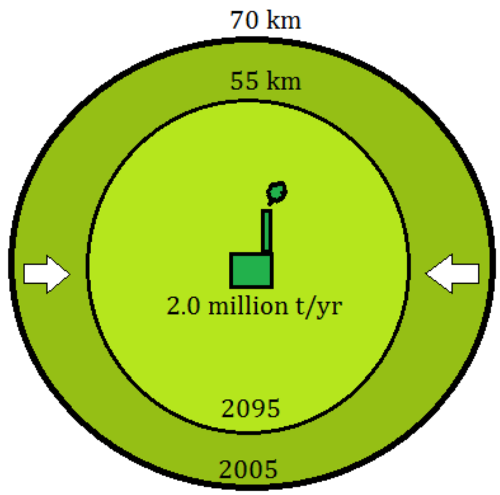
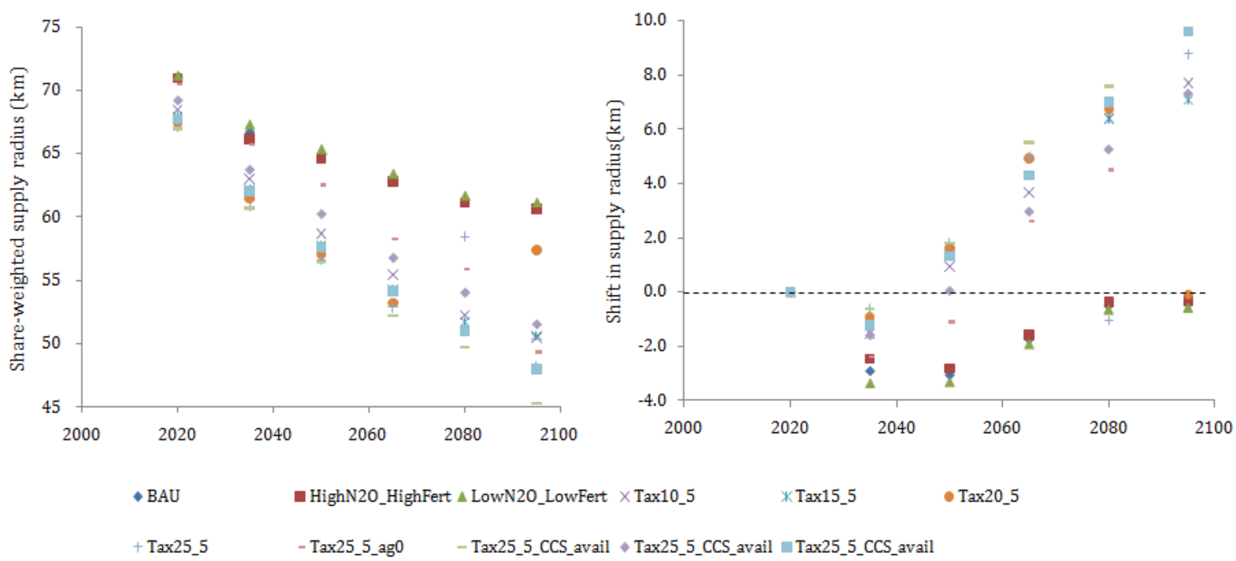



**Figure 3.9A/B. The effective supply radius over time across scenarios (8A). Figure shows that because of increasing yields, supply radius of biocrop cultivation will decline. Figure 8B shows the shift in supply radius relative to a "no crop movement" case.**



### 3.4 CONCLUSIONS

This paper is the first to examine contributions to long-term shifts in carbon intensity of bioenergy. I find that the carbon intensity of bioelectricity declines by about 50% between 2020 and 2095, while bioliquids and biogas remain relatively flat. These trends are a product of several effects. Although I model nitrogen application per GJ to be constant for a given AEZ over time, the shifting cultivation of biocrops between AEZs increases N2O emissions to about the year 2050 and decreases it thereafter. Similiarly, carbon intensities of bioenergy will decrease due to improved yields but this effect will be dampened before 2050 and accelerated after 2050 as effective yield of bioenergy moves towards less productive and more productive land, respectively. As yields increase, supply radii of bioenergy agrosystems decrease by an average of 21% across scenarios between 2020 and 2095 assuming an average input of 2.0 million tons of biomass $yr^{-1}$.

While some technical and spatial detail was sacrificed in order to conduct a global analysis, the value of this study to policymaking is to show that patterns in future bioenergy production have an effect on bioenergy's carbon intensity. To date, the emphasis of the literature on second-generation biofuels has been mainly comparing site-specific and feedstock-specific growing conditions, yields, nutrition, efficiencies, emissions, and energy use. Although this marks a reasonable starting place for research, the long-term attractiveness of a fuel should ultimately be measured in how it interacts with the energy and land-use system when it is greatly expanded. *GCAM* allows us to envision a number of different possible future and examine dynamics of the systems along those futures. Because *GCAM* includes both an agriculture and energy module within the model, there is opportunity to understand how changes in one system will relate to changes in the other.

There are a number of limitations to the study. Because of the exogenous assumptions on yield in *GCAM*, there is no opportunity for feedbacks between the climate system and agriculture system. Additionally, while *GCAM* uses a logit-share equation to create to determine market share of biocrops and end use technology and thus avoid winner-take-all projections, many of the parameters are characterized by point estimates which themselves have a high degree of uncertainty, in particular for bioenergy (Plevin et al., 2010). Another limitation is that I have not modeled country-level policies related to bioenergy. I also do not take account of the effect of feedstock on soil carbon. For example, there is evidence (Anderson-Teixiera et al., 2009; Cherubini et al., 2010) that perennial grasses enhance soil carbon if grown on marginal land and that the GHG savings could be substantial, at least in the short-run.

## 3.5 REFERENCES


Achten, W.M.J, Almeida, J., Fobelets, V., Bolle, E., Mathijs, E., Singh, V.P., Tewari, D.N., Verchot, L.V., Muys, B. 2010. Lifecycle assessment of jatropha biodiesel as transportation fuel in rural India, Applied Energy, 87, pp. 3652-3660.

Adegbidi, H.G., Briggs, R.D., Volk, T.A., White, E.H., Abrahamson, L.P., 2003. Effect of organic amendments and slow-release nitrogen fertilizer on willow biomass production and soil chemical characteristics. Biomass and Bioenergy, 25, pp. 389-398.

Adler P.R., Del Grosso S.J., Parton W.J. 2007. Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. Ecological Applications, 17, pp.675–691.

Anderson-Teixeira, K.A., Davis, S.C., Masters, M.D., DeLucia, E.H. Changes in soil organic carbon under biofuel crops. Global Change Biology, 1, pp. 75-96.

Boehmel, C., Lewandowski, I., Claupein, W. 2008. Comparing annual and perennial energy cropping systems with different management intensities. Agricultural Systems, 96, pp. 224-236.

Bouwman, A.F., Bournan, L.J.M., Batjes, N.H. 2002. Emissions of N2O and NO from fertilized fields. Summary of available measurement data. Global Biogeochemical Cycles, 16, pp. 1058-1069.

Brejda, J.J., Moser, L.E., Vogel, K.P. 1988. Evaluation of switchgrass rhizosphere microflora for enhancing seedling yield and nutrient uptake. Agronomy Journal, 90, pp. 753-758.

Brenkert, A.L., Kim, S.H., Smith, A.J., Pitcher, H.M. 2003. Model Documentation for the MiniCAM. U.S. Department of Energy Document, PNNL-14337.

Bruinsma, J. 2009. The Resource Outlook to 2050 – How Much Do Land, Water, and Crop Yields Need to Increase by 2050? United Nations Food and Agriculture Organization, Rome, Italy.

Cadoux, S., Riche, A.B., Yates, N.E., Machet, J.M. 2012. Nutrient requirements of miscanthus giganteus: conclusions from a review of published studies. Biomass and Bioenergy 38, pp. 14-22.

California Air Resources Board (CARB). 2013. Low Carbon Fuel Standard Program, Lookup Table. <http://www.arb.ca.gov/fuels/lcfs/lcfs.htm>.

Cassman, K.G. 1998. Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture. Proceedings of the National Academies of Science, 96, pp. 5952-5959.

Cassman, K.G., Doberman, A., Walters, D.T. 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. Ambio, 31, pp. 132-140.

Cavenaugh, A., Gasser, M.O., and M. Labrecque. 2011. Pig slurry as fertilizer on willow plantation. Biomass and Bioenergy, 35, pp. 4165-4173.

Cherubini, F., and G. Jungmeier. 2010. LCA of a biorefinery concept producing bioethanol, bioenergy, and chemicals from switchgrass. International Journal of Life Cycle Assessment, 15, pp. 53-66.

Davis, S., Parton, W., Dohleman, F., Smith, C., Del Grosso, S., Kent, A., and E. DeLucia. 2009. Comparative Biogeochemical Cycles of Bioenergy Crops Reveal Nitrogen-Fixation and Low Greenhouse Gas Emissions in a Miscanthus x giganteus Agro-Ecosystem. Ecosystems, Vol. 13, pp. 144-156.

DOE Hydrogen and Fuel Cells Program. 2013. DOE H2A Analysis. United States Department of Energy. Available at http://www.hydrogen.energy.gov/h2a_analysis.html.

EPA, 2006. Global Anthropogenic Non-CO2 Greenhouse Gas Emissions: 1990-2020. United States Environmental Protection Agency, EPA 430-R-06-003, June 2006. Washington, DC.

Ercoli, L., Mariotti, M., Masoni, A., Bonari, E. 1999. Effect of irrigation and nitrogen fertilization on biomass yield and efficiency of energy use in crop production of miscanthus. Field Crops Research 63, pp. 3-11.

Ericsson T. Nutrient cycling in energy forest plantations. Biomass and Bioenergy 1994;6:115–21.

Farrell, A. E., R. J. Plevin, B. T. Turner, A. J. Jones, M. O'Hare, and D. K. Kammen, 2006. Ethanol Can Contribute to Energy and Environmental Goals. Science 311, pp. 506-508.

Foley, J.A., N. Ramankutty, K.A. Brauman, E.S. Cassidy, J.S. Gerber, M. Johnston, N.D. Mueller, C. O'Connell, D.K. Ray, P.C. West, C. Balzer, E.M. Bennett, S.R. Carpenter, J. Hill, C. Monfreda, S. Polasky, J. Rockström, J. Sheehan, S. Siebert, D. Tilman and D.P.M. Zaks. 2011. Solutions for a cultivated planet. Nature 478(7369):337-342.

Forrester, D.I., Collopy, J.J., Beadle, C.L., Baker, T.G. 2011. Interactive effects of simultaneously applied thinning, pruning and fertilizer application treatments on growth, biomass production and crown architecture in a young Eucalyptus nitens plantation. Forest Ecology and Management, 267, pp. 104-116.

Goldemberg, J., Coelho Teixeira, S. 2004. Renewable energy – traditional biomass vs. modern biomass. Energy Policy 32, pp. 711-714.

Grisso, R., Perumproal, J.V., Vaughan, D., Roberson, G.T., Pitman, R. 2010. Predicting tractor diesel fuel consumption. Virginia Cooperative Extension, Publication 442-073.

Groode, T.A. J.B. Heyward. 2007. Ethanol: A Look Ahead. Massachusetts Institute of Technology, Publication number LFEE 2007-02 RP.

Havlik, P., Schneider, U.A., Schmid, E., Bottcher, H., Fritz, S., Skalsky, R., Aoki, K., De Cara, S., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., Obersteiner, M. 2011. Global land-use implications of first and second generation biofuel targets. Energy Policy, 39, pp. 5690-5702.

Heaton, E., Dohleman, F.G., Miguez, A.F., Juvik, J.A., Lozovaya, V., Widholm, J., Zabotina, O.A., Mcisaac, G.F., David, M.B., Voigt, T.B., Boersma, N.N., Long, S. 2008. Miscanthus: a promising biomass crop. Advances in Botanical Research, 56, pp. 76-137.

Heller, M.C., Keoleian, G.A., and T.A. Volk. 2003. Lifecycle assessment of a willow bioenergy cropping system. Biomass and Bioenergy, 25, pp. 147-165.

Hess, J.R., Kenney, K.L., Ovard, L.P., Searcy, E.M., Wright, C.T. 2009. Commodity-scale production of an infrastructure-compatible bulk solid from herbaceous lignocellulosic biomass. INL/EXT-09-17527.

Hill J, Nelson E, Tilman D, Polasky S, Tiffany D. 2006. Environmental, economic and energetic costs and benefits of biodiesel and ethanol biofuels. Proceedings of the National Academies of Science, 103, 30.

Himken M, Lammel J, Neukirchen D, Czypionka-Krause U, Olfs H-W. 1997. Cultivation of Miscanthus under West European conditions: seasonal changes in dry matter production, nutrient uptake and remobilization. Plant and Soil, 189, 117–126.

Hoefnagels, R. Smeets, E., and A. Faaij. 2012. Greenhouse gas footprints of different biofuel production systems. Renewable and Sustainable Energy Reviews, 14 pp. 1661-1694.

IEA, 2007. Tracking Industrial Energy Efficiency and CO2 Emissions. International Energy Agency. <http://www.iea.org/textbase/nppdf/free/2007/tracking_emissions.pdf>

International Fertilizer Association (IFA). 2013.
<IFA Statistics. http://www.fertilizer.org/HomePage/STATISTICS>

International Fertilizer Association (IFA) 2012. Increasing agricultural productivity to mitigate greenhouse gas emissions, IFA Document, July, 2012.

Intergovernmental Panel on Climate Change. 2006. Chapter 11: N2O Emissions from Managed Soils, and CO2 Emissions from Lime and Urea.

International Fertilizer Association (IFA). 2012. Increasing Agricultural Productivity to Mitigate Greenhouse Gas Emissions, Industry meeting, 2102.

Chum, H., A. Faaij, J. Moreira, G. Berndes, P. Dhamija, H. Dong, B. Gabrielle, A. Goss Eng, W. Lucht, M. Mapako, O. Masera Cerutti, T. McIntyre, T. Minowa, K. Pingoud. 2011. Bioenergy. In IPCC Special Report on Renewable. Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlomer, C. von Stechow (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Judd, T.S., Bennett, L.T., Weston, C.J., Attiwill, P.M., Whiteman, P.H. 1996. The response of growth and foliar nutrients to fertilizers in young Eucalyptus globules (Labill.) plantations in Gippsland, southeastern Australia. Forest Ecology and Management, 82, pp. 87-101.

Kendall, A. 2012. Time-adjusted global warming potentials for LCA and carbon footprints. International Journal of Life Cycle Assessment, 17, pp. 1042-1049.

Kim, S. Dale, B.E. 2008. Effects of nitrogen fertilizer application on greenhouse gas emissions and economics of corn production. Environmental Science and Technology, 42, pp. 6028-6033.

Kirkinen, J. 2009. Greenhouse impact assessment of some combustible fuels with a dynamic life cycle approach. Doctoral Dissertation. VTT Publications 773.

Kongshaug, G. 1998. Energy consumption and greenhouse gas emissions in fertilizer production. Publication for the International Fertilizer Association Technical Conference, Marrakech, Morocco, 28 September – 1 October 1998.

Krey, V., and L. Clarke. 2011. Role of renewable energy in climate mitigation: a synthesis of recent scenarios. Climate Policy, Vol. 11, pp. 1-28.

Kyle, P. 2012. Documentation of Fertilizer in GCAM. Document available upon request.

Kyle, P., Luckow, P., Calvin, K., Emanuel, W., Nathan, M., and Y. Zhou. 2011. GCAM 3.0 Agriculture and Land Use: Data Sources and Methods. PNNL-21025.

Ledin S. Management during the production period. In: Handbook for energy forestry. Uppsala, Sweden: Swedish University Agricultural Science, 1986. p. 19–20.

Lemus, R. Brummer, E.C., Burras, C.L., Moore, K.J., Barker, M.F., Molstad, N.E. 2008. Effects of nitrogen fertilizer on biomass yield and quality in large fields of established switchgrass in southern Iowa, USA.

Levasseur, A., Lesage, P., Margni, M., Samson, R. 2010. Biogenic carbon and temporary storage -addressed with dynamic life cycle assessment, Journal of Industrial Ecology, 17, pp. 117-128.

Lewandowski, I., Clinfton-Brown, J.C., Scurlock, J.M.O, Huisman, W. 2000. Miscanthus: European experience with a novel energy crop. Biomass and Bioenergy, 19, pp. 209-227.

Luckow, P. Wise, M.A., Dooley, J.J., Kim, S.H. 2010. Biomass energy for transport and electricity: large scale utilization under low CO2 concentration scenarios. U.S. Department of Energy document, PNNL-19124.

McLaughlin, S.B. and L.A. Kszos, 2003. Development of switchgrass (panicum virgatum) as a bioenergy feedstock in the United States. Biomass and Bioenergy, 28, pp. 515-535.

Melillo, J.M., Reilly, J.M., Kicklighter, D.W., Gurgel, A.C., Cronin, T.W., Paltsev, S., Felzer, B.S., Wang, X., Sokolov, A.P., Schlosser, C.A. 2009. Indirect emissions from biofuels: how important? Science, 326, 1397.

Miguez, F., Bonita Villamil, M., Long, S.P., and G.A. Bollero. 2008. Meta-analysis of the effects of management factors on miscanthus giganteus growth and biomass production. Agricultrual and Forest
Meterology, 148, pp. 180-1292.

Mitchell, C.P. 1995. New Cultural Treatments and Yield Optimisation. Biomass and Bioenergy, 9, pp. 11-34.

O’Hare M, Plevin RJ, Martin JI, Jones AD, Kendall A, Hopson E (2009) Proper accounting for time increases crop-based biofuels’green-house gas deficit versus petroleum. Environ Res Letters, 4.

Pandey, K.K., Pragya, N., Sahoo, P.K. 2011. Life cycle assessment of small-scale high-input jatropha biodiesel production in India. Applied Energy, 88, pp. 4831-4839.

Pedroso, G.M., De Ben, C., Hutmacher, R.B., Orloff, S., Putnam, D., Six, J., van Kessel, C., Wright, S., Linquist, B.A. 2012. Switchgrass is a promising, high-yielding crop for California biofuel. California Agriculture, 65, 3, pp. 168-173.

Pinkard, E.A., Baillie, C.C., Patel, V., Paterson, S., Battaglia, M., Smethurst, P.J., Mohammed, C.L., Wardlaw, T., Stone, C. 2006. Growth responses of eucalyptus globules Labill. To nitrogen application and severity, pattern, and frequency of artificial defoliation. Forest Ecology and Management, 229, pp. 378-387.

Plevin, R. J., M. O'Hare, A. D. Jones, M. S. Torn and H. K. Gibbs. 2010. The greenhouse gas emissions from market-mediated land use change are uncertain, but potentially much greater than previously estimated. Environmental Science & Technology, 44, pp. 8015-8021.

Rafiqul, I. Weber, C., Lehmann, B., Voss, A. 2005. Energy efficiency improvements in ammonia production – perspectives and uncertainties. Energy 30, pp. 2487-2504.

Richard, T. 2010. Challenges in scaling up biofuels infrastructure. Science, 329, pp. 793-796.

Schmer, M.R., Vogel, K.P., Mitchell, R.B., Perrin, R.K. 2007. Net energy of cellulosic ethanol from switchgrass. Proceedings of the National Academy of Science, 105, 2, pp. 464-469.

Schumaker, K. and J. Sathaye. 1999. India’s Fertilizer Industry: Productivity and Energy Efficiency. LBNL-41846.

Shield, I.F., Barraclough, T.J.P., Riche, A.B., Yates, N.E. 2012. The yield response of the energy crops switchgrass and reed canary grass to fertilizer application when grown on a low productivity sandy soil. Biomass and Bioenergy, 42, pp. 86-96.

Shinda, S. 2008. Options for a sustainable bioenergy: a jatropha case study. RIVM Report 607034001

Singh, B., Singh, K., Rao, G.R., Chikara, J., Kumar, D., Mischra, D.K., Saikia, S.P., Pathre, U.V., Raghuvanshi, N., Rahi, T.S., Tuli, R. 2011. Agro-technology of jatropha curcas for diverse environmental conditions in India. Biomass and Bioenergy,, 48, pp. 191-202.

Smeets, E.M.W, Lewandowski, I.M., Faaij, A. 2009. The economical and environmental performance of miscanthus and switchgrass production and supply chains in a European setting. Renewable and Sustainable Energy Reviews, 13, pp. 1230-1245.

Smeets, E.M.W., Bouwman, L.F., Stehfest, E., van Vuuren, D., Posthuma, A. 2009. Contribution of N2O to the greenhouse gas balance of first-generation biofuels. Global Change Biology, 15, pp. 1-23.

Smith, R. F.M. Slater. 2010. The effects of organic and inorganic fertilizer applications to miscanthus giganteus, Arundo donax and Phalaris araundinacea, when grown in energy crops in Wales, UK. Global Change Biology, 2, pp. 169-179.

Smith, C.M., David, M.B., Mitchell, C.A., Masters, M.D., Anderson-Teixeira, K.J., Bernacchi, C.J., DeLucia, E.H. 2013. Journal of Environmental Quality, 42, pp. 219-228.

Smethurst, P., Baillie, C., Cherry, M., Holz, G. 2003. Fertilizer effects on LAI and growth of four eucalyptus nitens plantations. Forest Ecology and Management, 176, pp. 531-542.

Snyder, C.S., T.W. Bruulsema, T.L. Jensen, and P.E. Fixen. 2009. Review of greenhouse gas emissions from crop production systems and fertilizer management effects. Agriculture, Ecosystems and Environment 133, pp. 247-266.

Sommerville, C., Youngs, H., Taylor, C., Davis, S.C., Long, S.P. 2010. Feedstocks for lignocellulosic biofuels. Science, 329, pp. 790-792.

Spatari, S., Zhang, Y., Maclean, H.L. 2005. Life cycle assessment of switchgrass and corn stover derived ethanol fueled automobiles, 39, pp. 9750-9758.

Stehfest, E., Bouwman, L. 2006. N2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. Nutrient Cycling in Agroecosystems, 74, pp. 207-228.

Stolarski, M.J., Szcukowski, S., Tworkowski, J., Klasa, A.J. 2011. Willow biomass production under conditions of low-input agriculture on marginal soils. Forest Ecology and Management., 262, pp. 1558-1566.

Taliaferro, 2002. Breeding and selection of new switchgrass varieties for increased biomass production. Oak Ridge National Lab report, ORNL/SUB-02-19XSY162C/01.

United Nations Environmental Program (UNEP). 2012. Global Environmental Facility (GEF) Project.
http://www.unep.org/bioenergy/Activities/TheGlobalEnvironmentFacilityGEFProject/tabid/79435/Default.aspx.

United Nations. 2013. UN Commodities Trade.
http://unstats.un.org/unsd/tradekb/Knowledgebase/UN-Comtrade-Reference-Tables.

U.S. Department of Agriculture (USDA). 2013. Fertilizer use and pricehttp://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx#.UaqgSJyGfjU

Uslu, A., Faaij, A.P., Bergman, P.C.A. 2008. Pre-treatment technologies, and their effect on international bioenergy supply chain logistics. Techno-economic evaluation of torrefaction, fast pyrolysis and pelletization. Energy, 33, pp. 1206-1223.

Vogel, K.P., Brejda, J.J., Walters, D.T., Buxton, D.R. 2002. Switchgrass biomass production in the Midwest USA: harvest and nitrogen management. Agronomy Journal, 9, pp. 413-420.

Wang, Z. and D.W. MacFarland. 2012. Evaluating the biomass production of coppiced willow and poplar clones in Michigan, USA, over multiple rotations and different growing conditions. Biomass and Bioenergy 46, pp. 380-388.

Wang, M. 2011. GREET 1.8c. Argonne National Laboratory, 2009. <http://greet.es.anl.gov/>

Willebrand, E., Ledin, S., Verwijst, T. 1993. Willow coppice systems in short rotation forestry: effects of plant spacing, rotation length and clonal composition on biomass production. Biomass and Bioenergy, 4, 5, pp. 323-331.

Wise, M., Calvin, K., Thomson, A., Clarket, L., Bond-Lamberty, B., Sands, R., Smith, S.J., Janetos, A., Edmonds, J. 2011. Implications of Limiting CO2 Concentrations for Land Use and Energy. Science, 324, pp. 1183-1186.

Wise, M. and K. Calvin. 2011. GCAM 3.0 Agriculture and Land Use: Technical Description of Modeling Approach. PNNL-20971.

Wright, M. Brown, R.C. 2007. Establishing the optimal sizes of different kinds of biorefineries. Biofuels, Bioproducts, Biorefineries, 1, pp. 191-200.

Zhou, W., Zhu, B., Li, Q., Ma, T., Hu, S., Griffy-Brown, C. 2010. Energy Policy, 38, pp. 3701-3709.