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Driving in Force: Why the U.S. Military Commutes by Automobile

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Driving in Force:

Why the U.S. Military Commutes by Automobile

by

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THESIS

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ABSTRACT
This paper explores the U.S. military's preference for commuting by automobile. After controlling for typical predictors of travel behavior such as socio-economic, demographic, family-related, immigration, transit availability, and built environment variables, military personnel are still more likely to drive to work than civilian counterparts. We investigate a number of incentives for driving to base such as discounted gasoline, free parking, and lack of walkability. We find that veterans have a greater likelihood of driving to work than civilian workers after controlling for the same predictors of travel, suggesting either a self-selection of auto-oriented individuals into the military or a "peer effect" whereby military individuals are conditioned to drive to work while in the military. We find evidence of the latter but cannot refute the former. An inherent bias towards consumptive behavior in the private lives of military members could have major implications for the military's overall energy use and environmental impact.

Keywords: military, mode choice, commute, travel behavior, DoD, IPUMS, Census

"The key to starting the creation of an energy-conscious mindset across the military rests in communicating the idea that behavior change on energy consumption is central to the military's organizational mission."

--Dr. Richard B. Andres, National War College; Micah Loudemilk, National Defense University, 2011--

I. INTRODUCTION

According to data from the U.S. Census Bureau (Ruggles et al., 2010), domestically-stationed U.S. military personnel have driven to work at higher rates than the non-military U.S. workforce since at least 1960, although the gap has narrowed considerably in the past two decades (Figure 1). Among those who drive to work, military personnel are also more likely to drive alone than their civilian counterparts are.

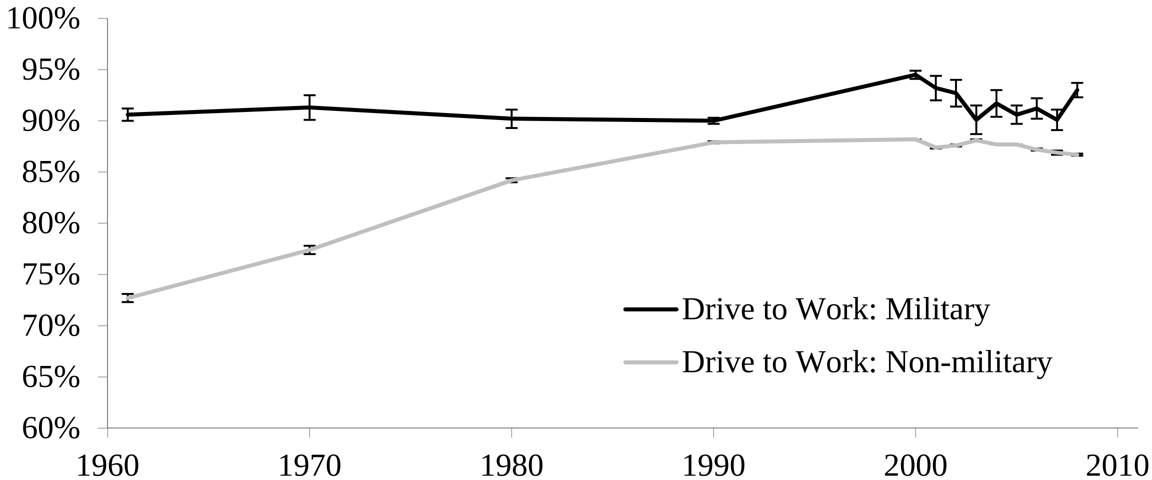

FIGURE 1: Percentage of Commuters Who Drive to Work 1960-2009 with 95% Confidence Intervals. Source: U.S. Census Bureau (Ruggles et al., 2010)

These trends have two implications for policy makers. First, driving generates a number of negative externalities in the forms of traffic congestion, air pollution, global climate change, traffic accidents, and dependence on foreign supplies of petroleum (Small and Kazimi, 1995; Parry et al., 2007; Lin and Prince, 2009; Leiby, 2007). These externalities represent a particular challenge for the Department of Defense given its size and geographic breadth: as the single largest employer in the U.S. with 1.4 million active duty members, 850,000 reservists, and 450,000 civilians, the DoD controls a land area roughly the size of Tennessee[1] which is scattered between 1,103 major geographic sites (DoD, 2009). Table 1 shows the number of installations by service and size of workforce. A recent National Academies of Science (NAS) study finds that metropolitan areas near military bases have faced "increased traffic congestion, greater traffic delays, and declining trip time reliability" (p. 82) and that "the military traditionally accepts no responsibility for traffic or environment problems outside of the gates of its bases" (p. 90) other

[1] This land area comparison is made using the "total acres" estimate of U.S./U.S. Territories in the 2009 Base Structure Report (DoD, 2009) of 27,921,165 acres. The U.S. Census (Ruggles et al., 2010) gives Tennessee's area as 26,971,520 acres.

than a rarely-used federal infrastructure fund.[2] The NAS report concludes that problems associated with military commuters are likely to compound as increasing numbers of overseas troops return home (NAS, 2011). Some features of military installations may actually incentivize auto use like discounted gasoline at base gas stations, free and abundant parking, and a lack of walkability. Understanding the correlates of driving among military members could help base and city planners improve on- and off-base transportation systems to better mitigate auto-born externalities. This study is the first to investigate factors that influence driving behavior members of the U.S. armed forces.

TABLE 1: Number of Installations by Military Workforce (DoD, 2009)[3]

	Number of Employees					
	>50,000	**25,000-49,999**	**10,000-24,999**	**1,000-9,999**	**<1,000**	**Total**
Air Force	0	0	0	130	187	317
Army	2	4	13	54	342	415
Marine	0	2	2	9	38	51
Navy	0	1	6	36	277	320
Total	2	7	21	229	844	1,103

A second – and arguably more significant -- policy implication of the military's personal travel behavior is that it may provide insights into the organization's total energy use. In 2010, the DoD used 890 x 10^{12} British Thermal Units (BTUs) of energy (DOE, 2011a), or about 1% of the U.S. total primary energy (DOE, 2011b) in pursuit of its operational goals. Of this energy, 80% was used in vehicles including planes, tanks, ships, and government automobiles (Coates, 2012). Although technological fixes to the military's energy challenges have become a focal point of military planning and acquisition in recent years, little interest has been given to behavioral aspects of energy use. A necessary question is: at an individual level do military members exhibit "overly" consumptive behavior? If inherent differences exist between military and civilian workers in how they use and perceive energy, then it is likely the DoD has an opportunity beyond technological fixes to reduce its energy use and environmental impact.

Below, we explore three questions related to military commuting. First, we investigate whether active duty and veteran military members drive more than civilian full-time workers after controlling for typical predictors of travel behavior such as socio-economic, demographic, family structure, immigration, transit availability, and land-use variables. We find strong evidence to indicate this is the case. Next, we examine whether specific factors on military bases such as total parking area, walkability, base gas stations, worker density, service affiliation (e.g. Navy), and the 2005 congressionally-mandated base realignment and closure (BRAC) which closed 33 installations and reassigned 123,000 troops, influence commute behavior of a military-only subpopulation. To do this, we utilize geographic workplace codes in the census to assign active military members to their respective home bases and exploit base-level variability in the

[2] This fund is called the Defense Access Roadways (DAR) and provides money for transportation projects outside US military bases. The stringency of DAR funding requirements means military bases rarely apply for it (NAS, 2011).

[3] Includes installations greater than 0.04 square km and over $10 million in building value.

above mentioned variables. Lastly, we attempt to show that driving to work is a learned trait within the military and present three pieces of supporting evidence.

II. BACKGROUND ON MILITARY INSTALLATIONS AND COMMUTING

A large fraction of current U.S. military bases were designed and built before the principles of compact development and Smart Growth were part of a developer's lexicon (Fig. 2). Bases were often hastily constructed during wartime which meant less attention could be paid to transportation infrastructure decisions and land-use planning. This was especially true during World War II, during which there was an increase in U.S. troop levels from 400,000 in 1939 to more than 8,000,000 in 1945 (U.S. Army, 1972). During this six-year time span, the U.S. Army Corps of Engineers built nearly 50% of currently operating installations (Evinger, 1998). Most bases follow similar geographic development patterns including 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.

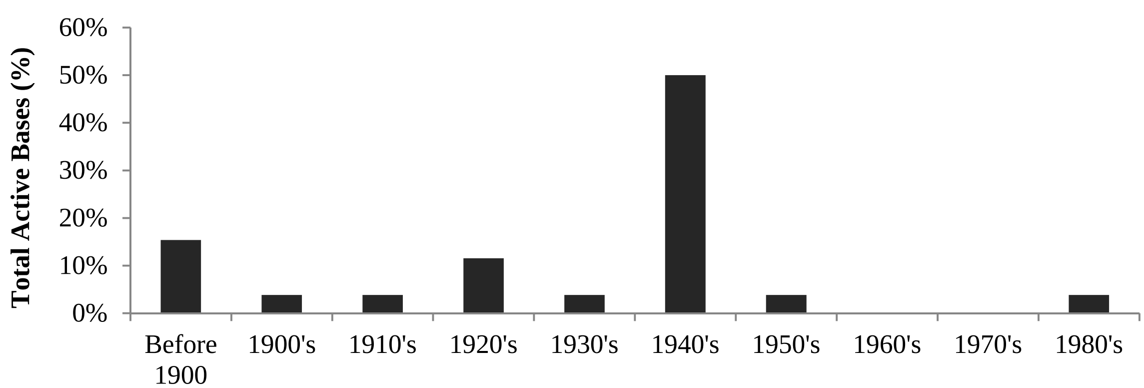

FIGURE 2
Construction Decade of Currently Active Military Bases in the Domestic U.S. (Evinger, 1998)

Two recent Executive Orders relate to employee commuting on military bases. In 2000, Executive Order 13150 sought "to reduce federal employees' contribution to traffic congestion and air pollution and to expand their commuting alternatives" by requiring federal agencies to provide public transit vouchers for their workforces (Federal Register, 2000). The DoD began the Transportation Incentive Program (TIP) in 2001, and offers up to $125 per month for workers to take trains, buses, ferries, or vanpools to work. We are unable to evaluate the TIP in our study because the program was enacted in 2001 and our dataset begins in 2006 so we do not have observations prior to the program's implementation. Moreover, data on this program is not available to the public.

The DoD also recently began tracking GHG emissions from employee commuting. Executive Order 13514, signed in 2009, requires federal agencies to conduct annual GHG emission inventories of employee commuting under "Scope 3 emissions" – those that result from

DoD activities but are not directly controlled by the DoD (Federal Register, 2009). Scope 3 emissions from employee commuting and deliveries. The agency set a reduction goal of 13.5% of these emissions between the 2008 baseline year and 2020 (DOE, 2011). However, the extent to which this policy will affect driving behavior on individual bases is likely minimal. Corporate Average Fuel Economy (CAFE) standards proposed by the U.S. Department of Transportation in 2011 will easily meet the emissions reduction goal.[4] Thus, the GHG reduction goal gives the appearance that the DoD is actively pursuing GHG goals whereas in reality the reductions are coming from external regulation.

III. DATA

Our main dataset comes from the 2006, 2007, 2008, and 2009 U.S. Census Bureau's American Community Survey (ACS), a nationwide survey which replaced the decennial long-form census after the year 2000.[5] The ACS's major advantages for this analysis over other travel data are the large sample sizes, the ability to conduct time series analyses, and the ability to identify active duty and retired military personnel (reservists are not counted as military personnel in this analysis). Person-level responses are available through the University of Minnesota's Integrated Public Use Microdata System (IPUMS) database (Ruggles et al., 2010). Individuals younger than 17 and older than 61 years were removed to correspond to military age requirements. Because our analysis includes a lagged variable, only the years 2007-2009 are used in models below.

The U.S. Census Bureau uses a multistage sampling design which includes stratification, clustering, and weighting of individuals. To help correct for the inherent homogeneity of individuals in the same household and geographic region, we 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 public use microdata area (PUMA)) is the stratum. PUMAs are the smallest identifiable geographic region in census data at the person-level and typically have ~100,000 people[6]. Other than the TSL procedure, other common methods for correcting standard errors in large survey data include Jackknife Repeated Replications (JRR) and Balanced Repeated Replications (BRR) (Chakrabarty, 1993). Empirical studies have shown that any of these methods can be used in analyses of complex survey data (Kish and Frankel, 1974; Bean, 1975). Since, JRR and BRR require considerably more computing power than the TSL, we chose to use the latter.

Our sample is comprised of three subgroups: full-time working civilians (n=2.5 million), full-time working veterans (n=116,784), and active duty military (n=9,602).[7] Models in Section V use all three groups while the models in Section VI and VII use only the active duty military

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[4] The Department of Transportation (DOT) proposed to increase the combined (light truck and passenger car) average fuel economy from 34.1 MPG in 2016 to 40.9 MPG in 2021. The DOT estimates this would reduce passenger car CO2 emissions 5% per year and light-duty truck emissions 3.5% per year (DOT, 2011).

[5] 2006 is the first year in our dataset because this was the first year with a full set of the variables mentioned below.

[6] Blumenberg and Evans (2010) outline two drawbacks of using census data to explain travel behavior besides the coarse geographic resolution: the journey to work is the only travel activity included in the survey and census data does not include information about amenities of different modes. We add to this list: no attitudinal information is available in census data.

[7] Reservists, Coast Guard, and National Guard members are not considered "active duty" in this analysis. Rather, the sample includes individuals who reported being on active duty in the Air Force, Army, Marine Corps, or Navy, and who can be tied to a specific military base.

subgroup. An important note is that none of the veterans commute to work in PUMAs with military bases, thus allowing us to separately identify the effects of having been in the military from the effects of commuting to a military base. This allows us to test whether commuting habits of military members persist after an individual separates from the military and are no longer affected by land use characteristics of bases.

This analysis does not consider military personnel who live in barracks, on ships, or in military prisons. According to data from the U.S. Census Bureau (Ruggles et al., 2010) this group, 35% of whom drive to work, comprises 23% of all military personnel. We remove the group because they have a fundamentally different home and work relationship than the rest of the military (i.e. they live at work). However, removing this group should not cause a residential self-selection problem after controlling for age, income, and education.[8] Military personnel in our dataset include personnel who either live in base housing (houses and apartment complexes located on the base) or in private residences offbase.

IV. Predictors of Commute Behavior

IV.A. Socio-Economic, Demographic, Family, and Immigration Variables

Military and civilian workers differ across a number of important individual characteristics, many of which also influence travel behavior. Nearly all studies of travel behavior control for socio-economic and demographic characteristics of the traveler. These characteristics typically include age, race, gender, education, and income and are strong predictors of travel behavior (Ewing and Cervero, 2001).

A number of recent studies also find a significant relationship between immigrant status and travel mode (Myers, 1996; Beckman & Konstandinos, 2008; Blumenberg & Evans, 2010; Tal & Handy, 2010). The most common measure of immigration status is the time in residence in the U.S. (Beckman & Konstandinos, 2008; Tal & Handy, 2010). Tal and Handy (2010) and Blumberg and Evans (2010) find that after living in the U.S. for five years, immigrants become more likely to commute by driving, while Myers (1996) reports the threshold at 10 years. We use the census question “years in the U.S.” to construct three immigration status dummy variables: immigrated 0-5 years ago, 6-10 years ago, and greater than 10 years ago.

One innovation in this paper is that, in addition to accounting for the birthplaces of foreign-born individuals, we also control for birthplaces within the U.S. by using regional birthplace dummy variables. Haustein et al. (2009) demonstrate how childhood and adolescence travel experiences can have strong impacts on actual and perceived use of cars in adulthood. These authors apply Baslington’s (2008) theory of childhood travel socialization which argues that socializing agents during childhood such as media, family, school, and peer groups can have significant impacts on an individual’s mode choice later in life. This finding is consistent with results from Johansson (2005) who shows that childhood experiences with traveling affect adults’ mode choice decisions. In total we have eleven geographic birthplace regions.

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[8] Age and seniority requirements for living in barracks or on ships differ by service and base. Typically, unmarried enlisted personnel in their first 4-6 years of active duty will be required to live in barracks or on ships. A self-selection problem would occur if individuals who prefer commuting by non-auto modes live in the barracks or on ships. However, since these living arrangements are mandatory, the non-barracks group should be a representative sample of military members after controlling for factors relating to their junior status such as age, education, and income.

While not present in every mode choice model, family-related variables such as marital status and number of children may help account for opportunity costs imposed by different modes of transport. Results are mixed as to whether these variables are significant predictors of travel behavior. Commins and Nolan (2011) estimate a multinomial logit model describing mode to work in the greater Dublin area. The reference mode is "car driver" and the dependent variable categories are walk, bike, bus, train, car passenger, and motorcycle. The authors use dummy variables for different age categories and find that most categories are statistically significant in each mode. On the other hand, Bento et al. (2005) find a weak and positive relationship between individuals with children between 5-21 years old and driving to work and Chatman (2002) finds no relationship between driving to work and having children under six. Also, Neog (2009) finds no relationship between driving to work and having children under 18. Some find individuals who are married are more likely to drive to work than non-married individuals (Commins and Nolan, 2011). Again, the military differs for most family variables. We also include a variable for the number of hours worked per week since longer hours at work could mean individuals would prefer fewer hours spent on his or her commute.

The two-sample t-tests of military and civilian worker populations in Table 2 highlight the importance of controlling for individual-level variables in an analysis of the military population, which differs significantly from the non-military population. A similar table comparing veterans and civilians is in Appendix I. When only considering the means, some of the more pronounced differences between military and civilians workers include the military's younger median age, larger proportion of males, and higher number of hours worked per week.

TABLE 2: Two Sample t-Tests of Military and Civilian Worker Populations (2007-2009 ACS)

	Civilian Workers n = 2,512,200				Military Workers n = 9,602				
	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Sig
Commute									
Drive to Work Frequency	0	1	0.89	0.31	0	1	0.96	0.20	****
Drive Alone to Work Frequency	0	1	0.80	0.30	0	1	0.88	0.27	****
Socio-economic / Demographic									
Age (years)	17	61	39.39	12.19	17	61	30.91	8.10	****
Family income ($10,000)	-3.1	137	6.65	6.06	0.06	48.9	5.17	3.40	****
Education level (years)	4	21	13.50	2.54	4	21	13.74	1.90	****
Female (dummy)	0	1	0.47	0.50	0	1	0.16	0.36	****
Race American Indian (dummy)	0	1	0.01	0.10	0	1	0.01	0.10	
Race White (dummy)	0	1	0.79	0.38	0	1	0.75	0.40	****
Race Black (dummy)	0	1	0.11	0.28	0	1	0.19	0.34	****
Race Pacific Islander (dummy)	0	1	0.002	0.05	0	1	0.006	0.08	****
Race Asian (dummy)	0	1	0.04	0.22	0	1	0.04	0.20	****
Race Other (dummy)	0	1	0.04	0.20	0	1	0.03	0.18	****
Born in Northeast Region (dummy)	0	1	0.12	0.31	0	1	0.09	0.29	****
Born in Mid-Atlantic Region (dummy)	0	1	0.13	0.12	0	1	0.13	0.12	
Born in East North Central Region (dummy)	0	1	0.20	0.23	0	1	0.15	0.18	****
Born in West North Central Region (dummy)	0	1	0.03	0.15	0	1	0.03	0.16	
Born in Southern Atlantic Region (dummy)	0	1	0.09	0.27	0	1	0.13	0.32	****
Born in East South Coast Region (dummy)	0	1	0.08	0.26	0	1	0.10	0.28	**
Born in South Coast West Region (dummy)	0	1	0.08	0.26	0	1	0.11	0.31	***

Born in US Mountain West states (dummy)	0	1	0.03	0.17	0	1	0.04	0.19	*
Born in US Pacific states (dummy)	0	1	0.12	0.31	0	1	0.15	0.35	****
Born in Latin America (dummy)	0	1	0.08	0.15	0	1	0.03	0.10	****
Born in West. Europe / Scandinavia (dummy)	0	1	0.01	0.10	0	1	0.02	0.13	****
Born in East Asian countries (dummy)	0	1	0.03	0.17	0		0.03	0.15	**
Immigration									
Immigrated to US 0-5 years ago (dummy)	0	1	0.02	0.13	0	1	0.01	0.07	****
Immigrated to US 5-10 years ago (dummy)	0	1	0.02	0.15	0	1	0.01	0.11	****
Immigrated to US >10 years ago (dummy)	0	1	0.08	0.30	0	1	0.06	0.26	****
Family									
Hours worked per week (hours)	1	99	39.90	11.89	0	99	51.30	13.76	****
Female worker with kids (dummy)	0	1	0.10	0.31	0	1	0.025	0.15	****
Family size (number)	1	31	2.69	1.49	1	12	2.50	1.44	****
Lifecycle: adult no kids (dummy)	0	1	0.60	0.49	0	1	0.55	0.50	****
Lifecycle: adult with kid(s) (dummy)	0	1	0.07	0.25	0	1	0.03	0.17	****
Lifecycle: 2 adults with kids (dummy)	0	1	0.32	0.47	0	1	0.42	0.49	****
Number of kids (number)	0	9	0.56	0.93	0	8	0.47	0.89	****

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 levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

IV.B. Built Environment Variables

The second category of predictor variables in most travel behavior models are those related to the geographic area in which the individual lives, works, and travels, often called "built environment" variables. Identifying relationships between the built environment and travel behavior is important as policymakers seek to reduce driving through new land development patterns. In the early 2000s, the land-use transportation literature was focused on understanding whether the built environment had a significant impact on travel behavior. Badoe and Miller (2000) present an extensive review of land-use travel literature up until the year 2000, concluding that a lack of consensus existed about this relationship. By the mid 2000s, the question no longer was whether the built environment had an effect on travel behavior -- one study states: "previous studies have provided ample evidence for the association between the built environment and travel behavior" (Cao et al., 2009, p. 798)) -- the question was how much variation in travel behavior could be attributed to the neighborhood self-selection effect versus the built environment (Handy et al., 2005; Mokhtarian and Cao, 2008). Zhou and Kockelman (2008) use Heckman's latent index model to show that the built environment explains over half of the differences in household vehicle miles traveled (VMT) in a sample of 1,903 households in Austin, Texas in 1998-1999. Bagley and Mokhtarian (2002) use structural equation modeling to test the relationship between the built environment of five San Francisco neighborhoods and household vehicle miles traveled. They find that attitudinal and lifestyle variables (i.e. self-selection) are far more important in predicting travel behavior than neighborhood built environment variables.

Often the built environment is quantified using densities such as population, employment, residential, or road density (see Cervero and Kockelman, 1997; Zhang, 2004; Heres-Del-Valle & Niemeier, 2011 for examples). While density variables sometimes fail to capture complex human travel behavior, some authors argue they act as reasonable proxies for important travel-related variables such as quantity of lower income households, parking supply, bus service availability, and mixed land uses (Steiner, 1994; Dunphy and Fisher, 1996). Other measures, such as the well-known "3 D's" (density, diversity, and design) put forth by Cervero and Kockleman (1997), use a combination of densities and indexes to measure the built environment. In an oft-cited paper, Bento et al. (2005) control for the built environment using road density, supply of rail, supply of bus transit, population centrality, jobs-housing balance, city shape and population density. Of these, only supply of rail transit, supply of bus transit, and road density are significant predictors of the drive-no drive decision to work.

Overlaying the discussion about the impact of the residential self-selection is a second discussion within the journey-to-work literature about the relative importance of characteristics of the residential versus workplace built environment. Some find that the workplace built environment has more impact on the mode to work than the household built environment (Crane and Crepeau, 1998; Ewing and Cervero, 2001; Zhang, 2004), while others find both built environments are important (Frank and Pivo, 1994).

Built environment variables in this paper are defined at the workplace and at the place of residence.[9] For 45% of observations these two take the same value because the individual works in the same PUMA as he/she lives. We construct a number of density variables using occupational codes. 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. This gives a reasonable measure of the availability of bus transit in both an individual’s workplace and residential PUMA. We do the same for other density measures including worker, renter, and subway/commuter train.[10] Obviously, many of these built environment variables are correlated. However, our large sample size provides ample variability across different built environments, and the coefficients we 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.

Table 3 compares military and civilian workers’ household and workplace built environment variables. A similar table comparing veterans and civilian workers is in Appendix I. As is evident, military workers tend to live and work in places with locations with lower worker and transit densities than civilians.

TABLE 3: Two Sample t-Tests For Military and Civilian Built Environments (2007-2009 ACS)

	Civilian Workers n = 2,512,200				Military Workers n = 9,602				
Variable	Min	Max	Mean	Std Dev.	Min	Max	Mean	Std Dev.	Sig
Residential PUMA									
Worker density (workers/sq. km)	0.2	156,495	1,755	6399.0	1.56	29,374	747.7	1598	****
Renter density (renters/sq. km)	0.009	43,317	572.9	1872.6	0.08	18,148	206.9	578.3	****
Bus density (bus workers/sq. km)	0	317	7.1	19.81	0.004	169	2.55	7.03	****
Subway density (subway workers/sq. km)	0	25	0.29	1.56	0	18	0.08	0.7	****
Lives in city center (dummy)	0	1	0.15	0.36	0	1	0.16	0.33	
Lives in rural area (dummy)	0	1	0.16	0.34	0	1	0.13	0.4	****
Lives in suburban area (dummy)	0	1	0.35	0.44	0	1	0.26	0.48	****
Lives in metropolitan area, land use type not specified (dummy)	0	1	0.34	0.47	0	1	0.45	0.5	****
Workplace PUMA									
Worker density (workers/sq. km)	0.2	156,495	3,360	15,135	1.16	17,606	1017.3	2437.3	****
Renter density (renters/sq. km)	0.005	30,074	421.3	2,512	0.18	3,445	85.5	294.9	****

[9] The only exception to this is a census-defined variable for residential community type: city center, rural, suburban, and land use not specified. We include these as dummy variables in all model specifications below.

Bus density (bus workers/sq. km)	0	317	10.4	33.67	0.005	169	3.4	9.12	****
Subway density (subway workers/sq. km)	0	25	0.52	2.67	0	18	0.14	0.863	****

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 levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

VI.C. Other Variables

We also control for regional differences in commute behavior through the use of nine regional and 51 state fixed effects. The regions include Northeast, Mid Atlantic, Midwest East North Central, Midwest West, North Central, South Atlantic, East South Central, West South Central, Mountain West, and Pacific West. Further, we account for the annual average snowfall and rainfall by state because, as shown by Bento et al. (2005), weather has been shown to relate to mode choice. Also, we include the log average gasoline price (DOE, 2010) to control for differences in the costs of driving and the average unemployment rate (BLS, 2011) by state and by year to control for the relative health of state economies. Below weather, gas price, and unemployment variables are referred to as "state-level variables." Finally, we control for the past driving behavior within PUMAs by lagging the driving frequency of both the residential and workplace PUMAs by one year.

V. MILITARY VERSUS CIVILIAN DRIVE TO WORK

V.A. Model

To investigate whether military members are inherently more likely to drive to work than civilians, we estimate a binary logit model that describes the drive-no drive decision for the working population in the U.S. (military and civilians) and that uses dummy variables for military and prior-military individuals:

Logit Model: $Pr_n = \frac{1}{1+e^{-z_n}}$,

where

$$z_n = f(M_n, V_n, SE_n, FA_{n,} IM_n, BE_n^h, BE_n^w, SL_n) \qquad (1)$$

where Pr_n is the probability of person *n* driving to work, z_n is the utility function for person *n* traveling between home and work, M_n is a dummy for whether individual *n* is in the military, V_n is a dummy for whether person *n* is a veteran (defined as anyone previously on active duty), SE_n are socio-economic variables of person *n*, FA_n are family variables of person n, IM_n are immigrant dummy variables categorized by time in residence in the U.S., BE_n^h are built environment variables for person *n*'s household PUMA, BE_n^w are built environment variables for person *n*'s workplace PUMA, and SL_n are state-level climate and economic indicators (seasonally adjusted unemployment rate, log of state average gas price) of person *n's* state of residence.

V.B. Results of General Population Model

Table 4 shows results for the Reference Case specification of Equation 1 and Table 5 is a robustness check for the military dummy variables using four other model specifications. In all the specifications attempted (even those not shown), the coefficients on being in the military are positive and significant at the 5% or better level. Moreover, the variables for veteran are also always positive and significant.

TABLE 4: Results for General Population Logit Model (Equation 1)

Dependent Variable: Drive to Work	Reference Case (Model 1)	
	Coeff.	Std. Err.
Military		
Military member in year 2007 (dummy)	0.559****	(0.132)
Military member in year 2008 (dummy)	1.052****	(0.147)
Military member in year 2009 (dummy)	0.619****	(0.091)
Veteran (separated >2 yrs ago) (dummy)	0.390****	(0.075)
Veteran (separated <2 yrs ago) (dummy)	0.140****	(0.012)
Family		
Years lived at current residence (years)	0.026****	(0.001)
Hours worked per week (hours)	0.009****	(3.2e-04)
Female employed worker (dummy)	0.094****	(0.006)
Female worker with kids (dummy)	-0.149****	(0.011)
Family size (number)	0.003	(0.003)
Vehicles per adult in household (number)	0.256****	(0.007)
Lifecycle: adult no kids (dummy)	0.270****	(0.027)
Lifecycle: 1 adult with kid(s) (dummy)	0.557****	(0.031)
Lifecycle: 2 adults with kid(s) (dummy)	0.436****	(0.029)
Number of children (number)	-0.052****	(0.005)
Immigration		
Immigrated to U.S. 0-5 years ago (dummy)	0.315****	(0.071)
Immigrated to U.S. 5-10 years ago (dummy)	0.696****	(0.071)
Immigrated to U.S. >10 years ago (dummy)	0.946****	(0.070)
Household Built Environment		
Workers density (workers/sq. km)	-3.61e-06****	(6.08e-07)
Renters density (renters/sq. km)	-1.31e-06****	(2.27e-06)
Bus density (bus workers/sq. km)	0.006****	(4.2e-04)
Train density (train workers/sq. km)	-0.001**	(0.003)
Lives in city center (dummy)	-0.102****	(0.011)
Lives in rural area (dummy)	0.061****	(0.010)
Lives in suburban area (dummy)	0.044****	(0.008)
Workplace Built Environment		
Worker density (workers/sq. km)	-1.09e-06	(9.48e-07)
Renters density (renters/sq. km)	-8.33-06***	(5.07e-06)
Bus density (bus drivers/sq. km)	0.002****	(3.79e-04)
Train density (train workers/sq. km)	0.011****	(0.003)
Lagged Drive Frequency Variables		
Household Lagged driving frequency	3.379****	(0.054)
Workplace Lagged driving frequency	5.181****	(0.060)
State-Level		
Annual avg. rainfall of state (inches)	0.002***	(5.6e-04)
Annual avg. snowfall of state (inches)	0.002****	(1.7e-04)
Log of avg. yearly gas price in state ($2009)	-1.396****	(0.194)

Annual unemployment rate for state (%)	0.024****	(0.003)
Controls for socio-economic/demographic variables	Yes	
Controls for region, birthplace, and year	Yes	
p-value (Pr > F)	0.0000****	
Observations	2,638,586	

Std. errors in parentheses
Significance levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

In Model 2, we remove the lagged drive frequency variable, but believe the model to be misspecified because the gasoline price variable is positive and significant, and because the lagged drive frequency variable has a significant coefficient in the other models when it is included. We therefore believe that the lagged drive frequency variable should be included in the model. This variable is discussed more in the military-only models in Section VI.

In Model 3, we change the income variable from log of income to income (in $10,000s). Doing so allows for the inclusion of approximately 30,000 observations with negative reported incomes (i.e. taking the natural log of negative values results in STATA dropping those observations).

In Model 4, we only consider heads of households. This is suggested by Marion and Horner (Marion & Horner, 2007) to help control for homogeneity among household members in their analysis of extreme commuters which uses similar 2000 census data. In Model 4, the magnitudes of the coefficients on the military variables are even larger than when using all working members of a household (Reference Case Model 1).

TABLE 5: Robustness Check for General Population Logit Model Showing Military and Veteran Dummy Variables (Equation 1)

Dependent Variable: Drive to Work	No Lagged (Model 2)		Income Changed (Model 3)		Heads of HH (Model 4)		No Birthplace Variables (Model 5)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Military in 2007 (dummy)	0.684****	(0.131)	0.554****	(0.132)	0.714****	(0.174)	0.549****	(0.132)
Military in 2008 (dummy)	1.184****	(0.147)	1.054****	(0.147)	1.336****	(0.194)	1.046****	(0.147)
Military in 2009 (dummy)	0.772****	(0.090)	0.604****	(0.091)	0.758****	(0.115)	0.613****	(0.090)
Veteran (Separated >2 yrs ago)	0.420****	(0.073)	0.395****	(0.075)	0.442****	(0.096)	0.391****	(0.075)
Veteran (Separated <2 yrs ago)	0.171****	(0.012)	0.140****	(0.012)	0.153****	(0.015)	0.139****	(0.012)
p-value (Pr > F)	0.000****		0.000****		0.000****		0.000****	
Observations	2,615,693		2,616,636		1,369,020		2,615,683	

Std. errors in parentheses
Significance levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

Although not shown, we found that removing the birthplace dummy variables results in two race variables becoming insignificant. Also, the omission changes the signs (but not significance levels) of two immigration status variables. This suggests that mode choice models are misspecified unless the model accounts for birthplace, or whatever variable birthplace is proxying. Also interesting is the fact that in the Reference Case model, the birthplace dummy for Mid Atlantic is positive and significant but the household regional dummy for Mid Atlantic is negative and significant. Even though models that do not include birthplace dummies appear to be misspecified, our result that the coefficients on being in the military are positive and significant is robust to removing the birthplace dummies (Model 5). These models support the conclusion of others that the more time an immigrant lives in the U.S., the more likely he is to travel by car (Tal & Handy, 2010). We also attempted specifications which interacted year with military service (e.g. Air Force*2009) and find that each of these interactions is positive and significant at the 5% level with the exception of Navy*2007 which is negative and not significant.

When using person-level census data the ideal method for controlling for differences in travel influences between different geographic regions using census data would be to use PUMA-level fixed effects. Unfortunately, given that the U.S. has over 1,500 PUMAs, we could not estimate this model because of insufficient computing power (although all our models have regional fixed effects as mentioned in Section VI.C). However, we attempted two smaller-scale models with PUMA-level fixed effects using the largest, smallest, and median sized bases (in terms of work population) for the Air Force, Army, Navy, and Marine Corps (Table 6). Like models 1-5, we included civilians, military, and veterans who worked at one of the 12 PUMAs. Again the coefficients on military and veteran were positive and significant at the 5% level. In a second model, we used the same set of PUMAs but also included the neighboring PUMAs. Thus, this model used fixed effects for the 12 regions rather than for the 12 PUMAs. Again, the coefficients on military and veterans were positive and significant at the 5% level.

TABLE 6: Twelve Example Bases in Dataset Ranked by Size of Military Workforce

Sample Bases	Base	Nearest Metro Area >100K people (distance in km)	Military Workers	Civilian Workers	Land Area (sq. km)	Reported Driving Frequency to Base	IPUMS Sample Size (weighted)
Air Force							
Smallest Base	Vance AFB	Ok City, OK (137)	666	160	15.1	100.0%	2 (215)
Median Base	Tyndall AFB	Tallahassee, FL (167)	3,925	732	116.6	98.9%	83 (6,920)
Largest Base	Lackland AFB	San Antonio, TX (21)	8,914	4,530	11.0	96.8%	323 (26,922)
Army							
Smallest Base	Anniston Depot	Birmingham, AL (85)	11	4,885	0.08	90.5%	10 (1,115)
Median Base	Fort Dix	Trenton, NJ (26)	3,961	1,068	0.13	90.2%	27 (2,584)
Largest Base	Fort Hood	Killeen, TX (11)	52,301	3,533	869.6	98.2%	478 (55,939)
Marine Corps							
Smallest Base	MCAS Yuma	SLR CO, Mexico (1)	3,623	426	32.2	100.0%	71 (11,201)
Median Base	Kaneohe MCB	Honolulu, HI (22)	6,575	525	12.0	94.0%	45 (4,844)
Largest Base	Pendleton SDMCTC	Wilmington, NC (84)	44,769	7,728	514.7	97.0%	501 (56,469)
Navy							
Smallest Base	NAS Meridian	Jackson, MS (179)	1,003	0	32.6	100.0%	10 (935)
Median Base	Corpus Christi	Corp. Christi, TX (29)	4,502	589	10.6	100.0%	18 (2,425)
Largest Base	Norfolk Naval Sta.	Norfolk, VA (16)	39,636	12,465	14.6	96.3%	536 (59,517)

V.C. Explanations for Higher Drive to Work Among Military

Three factors could explain why, at first glance, military individuals drive to work more than their civilian counterparts even after controlling for socio-economic, demographic and built environment variables. First, while our 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. Similarly, it is plausible that our land use variables lack enough geographic resolution to account for the transit options and built environment in and around military bases. Lastly, military members may have a different set of attitudes towards driving than civilians that manifest themselves in greater car use. These attitudes could be formed while individuals are in the military or could result from a self-selection of auto-oriented individuals. In the following sections, we include additional base-specific built environment variables and use a military-only population to explore the feasibility of the first two explanations. In Section VI, we explore the third.

VI. MILITARY ONLY MODEL

VI.A. Model and Variable Description

Table 6 above shows the smallest, median, and largest bases (ranked by size of military workforce) in our dataset for each service. In total we have data for 132 military installations. These bases have workforce sizes ranging between 11 and 52,301 troops and account for 1.01 million military members (or ~70% of the military workforce).

One key variable we explore is parking on bases. Not only do large surface parking lots increase the spatial separation between destinations, they may incentivize driving when they are free and abundantly available.[11] No study has been conducted on base parking or its effect on the military's transportation behavior. Among civilian commuters, Shoup (1997) demonstrated the considerable reductions in employee driving that can occur from removing an implicit free parking subsidy. Hess (2001) finds a statistically significant and negative relationship between parking price in downtown of Portland, Oregon and the likelihood of driving to work. Others, however, find a positive sign or an insignificant relationship between parking charge and likelihood to drive to work. Using data from the 1995 Nationwide Personal Transportation Survey, Chatman (2002) finds that paying to park at work has a positive and significant correlation with driving to work, concluding that confounding variables cause the positive sign. Neog (2009) also reports this unexpected directionality for employee commuting but also finds the relationship to be non-significant.

Since there is no variability between parking prices on bases (it's all free), we measure total available parking for each base using aerial photography available on ArcGIS Explorer (ESRI, 2010). All individuals on a base are assigned a base-specific parking area. Two measurement errors arise from our methodology: 1) we measure surface lot area but do not measure street parking. Thus, bases with a higher percentage of street parking relative to other bases will have an underestimated parking lot area estimate, and 2) parking garages are difficult to identify and measure using aerial photography. Again, bases with a relatively high percentage of parking garages will suffer from an underestimated parking lot area.

We use the Walk Score Index to measure the relative attractiveness of walking on base. Walk Score is an online tool originally developed for the real estate industry that captures the walkability to 13 non-work destinations including grocery stores, restaurants, bars, coffee shops, banks, movie theaters, parks, schools, fitness centers, drug stores, hardware stores, clothing stores, and book stores (Front Seat, 2010). We collect one Walk Score for each military base using the headquarters building address as the Walk Score geolocation. In a sample of 379 residential and non-residential addresses in Rhode Island, Carr et al. (2010) show that the Walk Score Index is a statistically valid measurement of distance to the thirteen amenities measured by the Walk Score index. Manaugh and El-Geneidy (2011) demonstrate that the Walk Score is the

[11] Occasionally parking spaces on bases will be restricted to a certain rank (e.g. space reserved for Colonels or higher), position (e.g. space reserved for ship's Captain), or vehicle type (e.g. space reserved for fleet maintenance vehicles).

best predictor of actual non-work walk trips among nine commonly used walkability indexes in Montreal, Quebec.

The discounted gasoline on bases could also serve as an incentive to drive. At each onbase station, station managers set the price of gasoline by surveying 5-10 civilian stations offbase. They then set prices at or slightly lower than the cheapest offbase station (Arakalian, 2010). Figure 4 shows the difference in retail unleaded gas prices for the main navy base in San Diego and the San Diego city-wide average. While this difference is only 11 cents per gallon, Figure 4 demonstrates that the difference hold relatively steady over time. We are currently unable to obtain gasoline prices for all military base gasoline stations, and therefore can only control for whether a gasoline station exists on the base or not. We create a binary variable, "Gas Station," that describes whether or not a gas station exists on a base according to the Military Travel Guide U.S.A (Crawford et al., 2010). Approximately 80% of military bases have military-owned gas stations (with discounted gasoline).

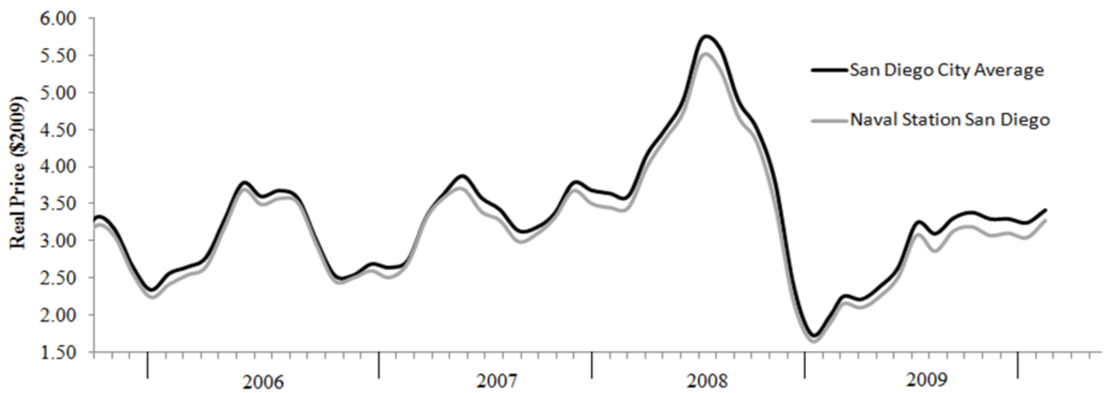

Figure 2: Difference Between San Diego City-Wide Average Regular Unleaded Retail Price and Naval Base San Diego (Arakalian, 2010; GasBuddy, 2010)

We create variables for base workforce and total land area of bases using data in the 2009 Base Structure Report (DoD, 2009). The workforce is the sum of civilian plus military workers on each base (since they both impact the road network). Also, we account for changes of a base's workforce caused by the 2005 Base Realignment and Closures (BRAC) – a congressionally-mandated closure of 33 bases and re-alignment (shift in troops) of 29 other bases – with the variables "Gaining" and "Losing", which measure the number of troops gained or lost, respectively. In total, 123,000 troops must move between bases. Data on the number of troops that were gained or lost by each base was taken from the BRAC Commission's final report to the President (BRAC, 2005).

Equation 2 has the same set of explanatory variables as Equation One but adds a set of base-specific variables and military-related variables.

Military-Only Logit Model: $Pr_n = \frac{1}{1+e^{-z_n}}$, where

$$z_n = f(SE_n, FA_n, IM_n, BE_n^h, BE_n^w, SL_n, BE_n^b, MIL_n) \qquad (2)$$

and where BE_n^b are the built environment characteristics of the person n's military installation and MIL_n are individual-level dummy variables for branch of armed service (Army, Navy) and rank (officer, enlisted).

VI.B. Results of Military-Only Model

Table 7 gives results of the reference case military-only logit model (Equation 2). All individuals in this subpopulation have been identified as working on one of the 132 military bases in our dataset. Several of the military-specific variables (both individual and base-specific) are significant or marginally significant suggesting that these variables should be included in the model. No workplace or military base built environment variables are significant at the 5% level. However, unlike the general population regressions in Section V, military commuters are more affected by residential PUMA. The negative and significant coefficient on the "Gaining" variable is robust across all specifications attempted. This fits well with the findings of NAS (2011), who describe increased congestion on bases that gained personnel in the 2005 BRAC.

TABLE 7: Military-Only Logit Model (Equation 2)

Dependent Variable: Drive to Work	**Military-Only Logit** (Model 6)	
	Coeff.	Std. Err
Family		
Years lived at current residence (years)	0.173***	(0.06)
Hours worked per week (hours)	-0.010*	(0.01)
Female employed worker (dummy)	0.289	(0.20)
Female worker with kids (dummy)	0.769	(0.53)
Family size (number)	-0.319***	(0.08)
Vehicles per adult in household (cars)	0.603****	(0.17)
Lifecycle: 1 adult no kids (dummy)	2.679***	(0.95)
Lifecycle: 1 adult with kid(s) (dummy)	2.524**	(1.07)
Lifecycle: 2 adults with kid(s) (dummy)	3.224***	(0.95)
Kids in household 5-21 years old (dummy)	-0.0183	(0.11)
Household Built Environment		
Worker density (workers/sq. km)	-0.0002****	(0.00)
Renter density (renters/sq. km	-0.00033***	(0.00)
Bus density (bus workers/sq. km)	0.0037	(0.02)
Train density (subway and train workers/sq. km)	0.1320	(0.13)
Lives in city center (dummy)	0.3740	(0.30)
Lives in rural area (dummy)	-0.1710	(0.37)
Lives in suburban area (dummy)	-0.1700	(0.20)
Lagged Drive Frequency Variables		
Household PUMA lag drive frequency	-0.7450	(2.40)
Workplace PUMA lag drive frequency	5.3840	(4.13)
Military Base lag drive frequency	2.583***	(0.97)
Workplace Built Environment		
Worker density (workers/sq. km)	-0.0001	(0.00)
Renters density (renters/sq. km)	0.0001	(0.00)
Bus density (bus workers/sq. km)	0.0155	(0.05)
Train density (subway and train workers/sq. km)	0.1860	(0.37)
Military Base Built Environment		
Walk Score (0-100 index)	-0.0002	(0.01)
Parking area of base (sq. km)	-0.000235*	(0.00)
Area of base (sq. km)	-0.0001	0.00

Number of employees at base (pos. integer)	1.81e-05*	(0.00)
On-base gas station? (dummy)	-0.2970	(0.36)
Military – other		
Troops gained at base in 2005 BRAC (pos. integer)	-7.33e-05**	(0.00)
Troops lost at base in 2005 BRAC (pos. integer)	7.11E-6	(0.00)
Marine Corps (dummy)	-0.3780	(0.36)
Air Force (dummy)	-0.0264	(0.29)
Navy (dummy)	-1.111***	(0.28)
Military Officer (dummy)	0.0189	(0.28)
Controls for socio-econ, demographic, immigration	Yes	
Controls for state-level variables	Yes	
Control for region, birthplace, year	Yes	
p-value (Pr > F)	0.0000****	
Observations	9,602	

Std. errors in parentheses
Significance levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

The dummy variable for *navy* is negative and significant suggesting differences between Navy and the reference service, Army. One possible explanation is that naval bases tend to be located in large metropolitan areas whereas army bases tend to be in more rural settings.

VII. MILITARY “PEER EFFECT”

VII.A. Evidence of Peer Effect

A casual observer might argue that differences between military and civilian commuters result from the different built environments the two groups must face on the way to their workplaces. However, results from above suggest that this is not the case. The most compelling support is that the dummy variables for *veteran* are positive and significant across specifications in the general population regressions (Tables 4 and 5). These individuals have civilian jobs located off base and therefore are not influenced by the military base built environment but do have a historical relationship with the military. Furthermore, in the military-only regression (Table 7) the only built environment variables that are even marginally significant are *base area* and *number of employees on base* and household built environment variables have higher significance levels than workplace or base-specific built environment variables. Together, these factors suggest something innate about the driving-centric nature of the military: either driving-prone individuals self-select into the military or the military conditions individuals to drive more. Below we present three pieces of evidence that support the latter explanation. Our data precludes us from empirically testing the first explanation but we include a brief discussion of its merits.

The first piece of evidence that military members are becoming driving-prone while in the military is the sign and significance levels of the *lagged driving frequency* variables. The lagged drive frequency of an individual’s residence, for example, is the total proportion of commuters who drove to work the previous year in the geographic area around the individual’s home. The workplace and residential lagged drive frequency attempt to get at the lagged effect of one’s “peers”. For the military population, in addition to the workplace PUMA lagged drive frequency, we use a variable for the base lagged drive frequency. As shown in Table 7 (and as verified with other model specifications not shown), the military base lagged drive frequency variable is positive and significant only at the military base level while for the general population this variable is positive and significant at for the residential and workplace PUMAs. This suggests that military personnel are being influenced by the past year's driving habits of other military personnel. The only weak point in this finding is that if a base-level variable that we do not control for (such as road width) has a significant impact on driving behavior, then we would expect that last year's driving frequency would also be related to an individual's commute decision this year.

Another measure of a "peer effect" is the contemporaneous driving habits of one's peers. Such an effect is challenging to evaluate because any factor that affects the driving habits of one's peers is also likely to affect his or her own. To overcome this endogeneity problem, we use an instrumental variable – *percent U.S. born by base* – which is highly related to the contemporaneous frequency of driving to a particular base by peers but is not related to whether or not a specific individual on that base drives. We estimate IV probit and IV regression models using the same variables as the military-only logit model in Equation 2. In both models, the variable *base driving frequency* is positive and significant meaning that, all else equal, a higher driving rate of your peers will cause you to drive more. In Table 8 we present model results of the first-stage regression. The instrument has an F-statistic of 587. Probit and linear regression models using the instrumental variable are presented in Table 9.

TABLE 8: First-Stage Regression Model of Military-Only Population

Dependent Variable: Frequency of Driving to Base	(Model 7)	
	Coeff.	Std. Err
Instrument variable		
Percent U.S. Born on Base (%)	0.482***	(0.02)
Family		
Years lived at current residence (years)	-0.000575	(0.00)
Hours worked per week (hours)	9.53E-05	(0.00)
Female employed worker (dummy)	-0.000469	(0.00)
Female worker with kids (dummy)	0.00258	(0.01)
Family size (number)	-0.000678	(0.00)
Vehicles per adult in household (cars)	0.00024	(0.00)
Lifecycle: 1 adult no kids (dummy)	-0.0365	(0.02)
Lifecycle: 2 adult with kid(s) (dummy)	-0.0328	(0.02)
Kids in household 5-21 years old (pos. integer)	-0.00322*	(0.00)
Household Built Environment		
Worker density (workers/sq. km)	2.34E-06	(0.00)
Renters (renters/sq. km)	9.34e-06***	(0.00)
Train density (train workers/sq. km)	-0.000188	(0.00)
Bus density (bus workers/sq. km)	-0.000261	(0.00)
Lives in city center (dummy)	0.000847	(0.00)
Lives in rural area (dummy)	0.00911***	(0.00)
Lives in suburban area (dummy)	-0.0012	(0.00)
Workplace Built Environment		
Worker density (workers/sq. km)	-4.31E-06	(0.00)
Renter density (renters/sq. km)	-0.00024****	(0.00)
Train density (subway and train workers/sq. km)	0.0216****	(0.01)
Bus density (bus workers/sq. km)	0.00421****	(0.00)
Lagged Drive Frequency Variables		
Household PUMA lag drive frequency	0.116****	(0.03)
Workplace PUMA lag drive frequency	0.209****	(0.06)
Military Base Built Environment		

Walk Score (0-100 index)	2.62E-05	(0.00)
Parking area of base (sq. km)	1.14e-08****	(0.00)
Area of base (sq. km)	-6.58e-06****	(0.00)
Number of employees at base (pos. integer)	7.06e-07****	(0.00)
On-base gas station? (dummy)	0.0209****	(0.00)
Troops gained at base in 2005 BRAC (pos. integer)	-4.98E-07	(0.00)
Troops lost at base in 2005 BRAC (pos. integer)	-3.84e-06****	(0.00)
Military – other		
Senior (dummy for >2 years in the service)	0.00024	(0.00)
Marine Corps (dummy)	-0.0116**	(0.00)
Air Force (dummy)	0.0118****	(0.00)
Navy (dummy)	-0.0135****	(0.00)
Military Officer (dummy)	-8.90E-05	(0.00)
Constant	-2.098***	(0.53)
Controls for socio-econ, demogrph, immig.	Yes	
Controls for state-level variables	Yes	
Control for region, birthplace, year	Yes	
p-value (Pr > F)	0.0000****	
Observations	1,876	

Std. errors in parentheses
Significance levels: *p<0.05, **p<0.01 ***p<0.001, ****p<0.0001

The last piece of evidence that the individuals become more prone to driving while in the military is a variable that describes the length of time an individual has served in the military – *senior*. Specifically, this dummy variable takes the value of "1" if an individual has served more than 2 years active duty and zero otherwise. The general population and military-only models do not include this variable because the Census Bureau stopped collecting it in 2007 and therefore was only available for one year of our data. The *senior* variable is included in both the IV regression and IV probit models below and is significant and positive in both suggesting that, after controlling for other status-related factors such as age, income, and rank, the longer a service member spends in the military the more likely he or she is to drive.

TABLE 9: IV Probit and IV Regression Models

Dependent Variable: Drive to Work	**IV Probit** (Model 8)		**IV Regression** (Model 9)	
	Coeff.	Std. Err	Coeff.	Std. Err
Instrumented variable				
Base driving frequency (%)	4.100**	(2.00)	0.667***	(0.21)
Family				
Years lived at current residence (years)	0.058	(0.05)	0.00159	(0.00)
Hours worked per week (hours)	-0.006	(0.00)	-0.0005*	(0.00)
Female employed worker (dummy)	0.059	(0.21)	0.00842	(0.01)
Female worker with kids (dummy)	0.276	(0.38)	0.0053	(0.03)
Family size (number)	-0.24***	(0.09)	-0.029****	(0.01)
Vehicles per adult in household (cars)	-0.032	(0.11)	-0.00392	(0.01)
Lifecycle: 1 adult no kids (dummy)	2.516	(1.25)	0.518****	(0.12)
Lifecycle: 2 adults with kid(s) (dummy)	2.142*	(1.26)	0.553****	(0.12)
Kids in household 5-21 years old (pos. integer)	0.162	(0.11)	0.0211**	(0.01)
Household Built Environment				
Worker density (workers/sq. km)	-1.58e-04	(0.00)	-2.5e-05***	(0.00)
Renter density (renters/sq. km)	-3.98e-04**	(0.00)	-2.63e-05*	(0.00)
Train density (train workers/sq. km)	-0.073	(0.18)	-0.0178	(0.02)

Bus density (bus workers/sq. km)	0.029	(0.03)	0.00645**	(0.00)
Lives in city center (dummy)	0.300	(0.27)	0.0253	(0.02)
Lives in rural area (dummy)	-0.0452	(0.26)	-0.00103	(0.02)
Lives in suburban area (dummy)	-0.221	(0.17)	-0.0147	(0.01)
Workplace Built Environment				(0.00)
Worker density (workers/sq. km)	-0.000254	(0.00)	7.50e-07	(0.00)
Renter density (renters/sq. km)	0.00299	(0.00)	-4.67e-06	(0.00)
Train density (train workers/sq. km)	-0.048	(0.08)	-0.00732	(0.01)
Bus density (bus workers/sq. km)	0.715	(0.46)	0.0960***	(0.03)
Lagged Drive Frequency Variables				(0.02)
Household PUMA lag drive frequency	-1.187	(2.13)	-0.0681	(0.17)
Workplace PUMA lag drive frequency	1.139	(3.88)	-0.0988	(0.29)
Military Base Built Environment				
Walk Score (0-100 index)	-2.35e-04	(0.00)	1.82e-05	(0.00)
Parking area of base (sq. km)	-6.16e-07**	(0.00)	-4.4e-08**	(0.00)
Area of base (sq. km)	-9.43e-05	(0.00)	-3.77e-06	(0.00)
Number of employees at base (pos. integer)	1.71e-05**	(0.00)	9.24e-07	(0.00)
On-base gas station? (dummy)	0.0324	(0.31)	-0.00956	(0.02)
Troops gained at base in 2005 BRAC (pos. integer)	-4.69e-05	(0.00)	-2.89e-06	(0.00)
Troops lost at base in 2005 BRAC (pos. integer)	4.51e-05	(0.00)	-7.68e-07	(0.00)
Military – other				
Senior (dummy for >2 years in the service)	0.366**	(0.21)	0.0469****	(0.02)
Marine Corps (dummy)	-0.484	(0.31)	-0.0382	(0.02)
Air Force (dummy)	0.039	(0.24)	-0.00967	(0.02)
Navy (dummy)	-0.500**	(0.21)	-0.0392**	(0.02)
Military Officer (dummy)	-0.202	(0.25)	-0.0195	(0.02)
Controls for socio-econ, demogrph, immig.	Yes		Yes	
Controls for state-level variables	Yes		Yes	
Control for region, birthplace, year	Yes		Yes	
p-value (Pr > chi^2)	0.0000****			
R-squared			0.1288	
Observations	1,876		1,876	

Std. errors in parentheses

Significance levels: *p<0.1, **p<0.05 ***p<0.01, ****p<0.001

VIII.B. Discussion

The nature of the military's socialization process could help explain the military's driving peer effect. Socialization refers to the process through which an individual learns a common organizational or group culture. Military socialization begins in the indoctrination period (bootcamp or officer training) in which individuals are subjected to stresses meant to emulate the battlefield (Katzenstein and Reppy, 1999). Individuals work, sleep, and eat with their peers. Kier comments, "This initiation process is specifically designed to provide the kind of intensive experience that will encourage the inductee to forego his or her individual and civilian identity and replace it with a corporate spirit or esprit de corps" (p. 28, Kier, 1999). The military has been described as a "greedy organization" because of the level of commitment expected from its personnel and the lack of control available to the personnel and their families (Coser, 1974; Segal, 1986). Soldiers learn they are expected to conform or quit. The idea that military peers can act as agents of travel socialization fits well with research from Haustein et al. (2008) who use structural equation modeling to demonstrate that young adolescents are affected by mode choice decisions of their peer group. It is reasonable to imagine that driving has become wrapped up in the socialization process and is now a dominant social norm. Individuals might learn that driving to work is an important aspect of good soldiering.

In addition to peer influence, there may be unobservable individual characteristics that we do not control for that could affect driving behavior and that are more prevalent among military workers. One such variable is masculinity. The sociologists Katzenstein and Reppy (1999) state, “Studies of militaries invariably allude to the conventional equating of good soldiering with masculinity” (p. 8). Troops are expected to embody the “combat, masculine warrior paradigm,” which Dunivan (p. 534, 1994) describes as “the essence of military culture.” Only recently have women joined the armed forces in considerable numbers meaning the culture is largely shaped by men. Still, only 16% of the military is women and some combat communities still exclude women. Even the uniforms are constructed to imbue individuals with a physical appearance of “maleness” (Katzenstein and Reppy, 1999). Masculinity is often linked to automobile use. Masculinity has been positively related to the number of miles driven per year (Ozkan and Lajunen, 2005), an increase in aggressive driving behavior in young men (Krahe and Fenske, 2002; Mast et al., 2008), and an increase in driving skills (Ozkan and Lajunen, 2006). If more masculine individuals are entering the armed forces, then, since more masculine individuals are more likely to drive, those in the armed forces will be more likely to drive.

Another unobservable characteristic that may cause the military population to drive more than the civilian population is the desire for individualism outside of the workplace. Stradling et al. (2000) find that the car provides a sense of freedom, self-confidence, and control while public transit does not. Others have demonstrated that the car is a symbolic icon that enables expressions of individualism and autonomy (Steg et al., 2001; Steg, 2005). High auto-use may be a manifestation of the individual liberty for which many individuals consider worth fighting. Similarly, it is possible that driving is a response to the somewhat confining culture of the military. A feeling of entrapment during the workday may lead to individual expressions of freedom outside of the workplace. If those who join the military have a greater desire for individualism outside of the workplace, then this may explain why those in the military drive more. However, if those in the military do cherish their individualism, then we would not expect to see a peer effect, since individualists are less likely to want to mimic their peers. Our results supportive of a peer effect suggest that the peer effect may be more important than individualism in explaining why the military population drives more.

IX. CONCLUSION

We have shown the military’s journey to work differs significantly from civilian workers after controlling for important influences on commute mode. Troops become more likely to drive the longer they stay in service and their likelihood of driving stays elevated after they separate from the military. With 21.8 million veterans in the U.S. (Ruggles, 2011), the effects of a learned driving behavior could have impacts outside of the activity duty military. Our analysis suggests that military members are being influenced by past and present driving behavior of their peers stationed on the same base. If this peer effect exists in other realms within military life, then reducing the DoD’s annual energy consumption may be a particularly difficult endeavor and may require behavioral fixes in addition to the current DoD strategy of using technological fixes.

REFERENCES

Arkalian, Arman. Personal interview with Automotive Service Manager, Navy Exchange, San Diego, CA area. (Mr. Arkalian manages and sets prices at 10 gas stations in the San Diego area), 2010.

Badoe, Daniel A., and Eric Miller, "Transportation-land-use interaction: empirical findings in North America, and their implications for modeling," *Transportation Research Part D*, 5 (2000), 235-263.

Bagley, Michael N., and Patricia L. Mokhtarian, "The Impact of Residential Neighborhood Type on Travel Behavior: A Structural Equations Modeling Approach," *Annals of Regional Science,* 36 (2002), 279–297.

Coates, Julius, "Challenge of Reducing Energy Consumption and Improving Energy Efficiency and the Impact on Military Operations and Readiness," Presentation at the 91st Transportation Research Board Conference, Washington D.C., January, 2012.

Baslington, H., "Travel socialization: A social theory of travel mode behavior," *International Journal of Sustainable Transportation*, 2 (2008), 91–114.

Bean, J.A., "Distribution and Properties of Variance Estimators for Complex, Multi-Stage Probability Samples," *Vital and Health Statistics*, Series 2, No. 65, U.S. Government Printing Office, Washington DC, 1975.

Beckman, J.D. and G.G. Konstandinos, "Immigration, residential location, car ownership, and commuting behavior: a multivariate latent class analysis from California," *Transportation*, 35 (2008), 655-671.

Bento, Antonio M., Maureen L. Cropper, Ahmed Mushfiq Mobarak, and Katja Vinha, "The Effects of Urban Spatial Structure on Travel Demand in the United States," *Review of Economics and Statistics*, 87 (2005), 466-478.

Blumenberg, Evelyn, and Alexandra Elizabeth Evans, "A.E. Planning for Demographic Diversity: The Case of Immigrants and Public Transit," *Journal of Public Transportation*, 13 (2010), 23-45.

BRAC Commission, "2005 Defense Base Closure and Realignment Commission Final Report to the President," 2005, http://www.brac.gov/finalreport.html, Accessed May 20, 2011.

Bureau of Labor Statistics (BLS), "Local Area Unemployment Statistics: Current Unemployment Rates for States and Historical Highs/Lows," 2011, http://www.bls.gov/lau/tables.htm. Accessed March 13, 2011.

Cao, Xinyu (Jason), Patricia L. Mokhtarian, and Susan L. Handy, "Examining the Impacts of Residential Self-Selection on Travel Behavior: A focus on Empirical Findings," *Transport Reviews*, 29 (2009), 359-395.

Carr, Lucas J., Shira L. Dunsiger, and Bess Marcus, "Validation of Walk Score for Estimating Access to Walkable Amenities," *British Journal of Sports Medicine*, 10 (2010), 1-5.

Cervero, Robert, and Kara Kockelman, "Travel Demand and the Three Ds: Density, Diversity, and Design." *Transportation Research Part D*, 2 (1997), 199–219.

Chakrabarty, Rameswar P., "Variance Estimation by Users of SIPP Micro-Data Files." U.S. Census Research Report 93-06, 1993.

Chatman, Daniel G., "How Density and Mixed Uses at the Workplace Affect Personal

Commercial Travel and Commute Mode Choice," *Transportation Research Record,* 1831 (2002), 193-201.

Commins, N. and A. Nolan, "The Determinants of Mode of Transport to Work in the Greater Dublin Area." *Transport Policy*, 18 (2011), 259-268.

Coser, Lewis, "Greedy Institutions: Patterns of Undivided Commitment," (Free Press: New York, 1974).

Crane, R. and R. Crepeau,"Does neighborhood design influence travel? A behavioral analysis of travel diary and GIS data," *Transportation Research D*, 3-4 (1998), 225-238.

Crawford, William, L. Ann Crawford, and R.J. Crawford, "Military Travel Guide U.S.A." (Military Living Publications: Washington D.C., 2010).

Department of Defense (DoD), "2009 Base Structure Report," Office of the Deputy Under-Secretary of Defense for Installations and Environment, 2009, http://www.defense.gov/pubs/pdfs/2009baseline.pdf, Accessed July 1, 2011.

Department of Defense (DoD). "Department of Defense Annual Energy Management Report Fiscal Year 2010." Office of the Deputy Undersecretary of Defense, 2010. http://www.acq.osd.mil/ie/energy/energymgmt_report/main.shtml, Accessed March 15, 2011.

Department of Energy (DOE), "State Energy Data Systems (SEDS), Table 10 F11a: Total Petroleum Consumption Estimates by Sector, 2010" Energy Information Administration, 2010, www.eia.doe.gov/emeu/states/hf.jsp?incfile=sep_fuel/html/fuel_Use_pa.html. 12, Accessed March 3, 2010.

Department of Energy (DOE), 2011a, "Table 1.13 U.S. Government Energy Consumption by Agency and Source, Fiscal Years 2003, 2009, 2010," Energy Information Administration, http://www.eia.gov/totalenergy/data/annual/txt/ptb0113.html, Accessed April 1, 2011.

Department of Energy (DOE), 2011b, "Table 10: Energy Consumption by Sector and Source. Annual Energy Outlook, 2011," U.S. Energy Information Administration, http://205.254.135.24/forecasts/aeo/tables_ref.cfm, Accessed March 2, 2011.

Department of Transportation (DOT). 2011. "2017-2025 Model Year Light-Duty Vehicle GHG Emissions and CAFÉ Standards: Supplemental Notice of Intent," National Highway Traffic Safety Administration (NHTSA), http://www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/SNOI_2_for_2017on-09Aug11.pdf, Accessed September 12, 2011.

Dunivan, K.O., "Military culture: change and continuity,*"* *Armed Forces and Society*, 20 (1994), 531-547.

Dunphy, R. T., and K. Fisher, "Transportation, Congestion, and Density: New Insights," In *Transportation Research Record,* 1552 (1996), 89–96.

ESRI. 2010. "ArcGIS Explorer Online." http://explorer.arcgis.com. Accessed Dec. 12, 2010.

Evinger, W. 1998. "Directory of U.S. Military Bases Worldwide, 3rd Edition." (Oryx Press: Phoenix AZ).

Ewing, Reid and Robert Cervero, "Travel and the Built Environment: A Synthesis, *Transportation Research Record,* 1780 (2001), 87-114.

Federal Register. 2000. "Executive Order 13150. Federal Workforce Transportation." Available at: http://frwebgate.access.gpo.gov/cgi-bin/getdoc.cgi?dbname =2000_register&docid=fr26ap00-131.pdf. Accessed March 23, 2011.

Federal Register. 2009. "Executive Order 13514: Federal Leadership in Environmental, Energy, and Economic Performance." http://edocket.access.gpo.gov/2009/pdf/E9-24518.pdf. Accessed March 3, 2011.

Frank, L.D, and G. Pivo, “Impacts of Mixed Use and Density on Utilization of Three Modes of Travel: Single-Occupant Vehicle, Transit, Walking,” *Transportation Research Record*, 1466 (1994), 44-52.

Front Seat. 2011. “Walk Score Methodology.” http://www2.walkscore.com/pdf/WalkScoreMethodology.pdf. Accessed May 2, 2011.

GasBuddy. 2011. “Historical San Diego Gas Prices.” purchased dataset from www.sandiegogasprices.com/Retail_Price_Chart.aspx.

Handy, Susan, Xinyu (Jason) Cao, and Patricia L. Mokhtarian, “Correlation or Casualty between the Built Environment and Travel Behavior? Evidence from Northern California,” *Transportation Research Part D*, 10 (2005), 427-444.

Haustein, Sonja, Christian A. Klockner, and Anke Blobaum, “Car use of young adults: The role of travel socialization,” *Transportation Research Part F*, 12 (2009), 168-178.

Heres-Del-Valle, David, and Deborah Niemeier, “CO_2 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 (2011), 150-161.

Hess, Daniel B, “Effect of Free Parking on Commuter Mode Choice: Evidence from Travel Diary Data,” *Transportation Research Record*, 1753 (2001), 35-42.

Johansson, M., T. Heldt, and P. Johansson, “The Effects of Attitudes and Personality Traits on Mode Choice,” *Transportation Research Part A*, 40 (2006), 507-525.

Katzenstein, M. and J. Reppy, “Beyond Zero Tolerance: Discrimination in Military Culture,” (pp. 1-21, Rowman and Littlefield Publishers, Inc:, Lanham, MD, 1999).

Kier, Elizabeth, “Beyond Zero Tolerance: Discrimination in Military Culture,” (pp. 25-52, Rowman and Littlefield Publishers, Inc:, Lanham, MD, 1999).

Kish, L. and M.R. Frankel, “Inference from Complex Samples,” *Journal of the Royal Statistical Society*, *Series B*, 36 (1974), 1-37.

Krahe, B., and I. Fenske, “Predicting Aggressive Driving Behavior: The Role of Macho Personality, Age, and Power of Car,” *Aggressive Behavior*, 28 (2002), 21–29.

Leiby, Paul, 2007, “Estimating the Energy Security Benefits of Reduced U.S. Oil imports. Oak Ridge National Laboratory,” ORNL/TM-2007/028.

Lin, C.-Y. Cynthia and Lea Prince, “Optimal Gas Tax in California,” *Energy Policy*, 37 (2009), 5173-5183.

Manaugh, K., and A. El-Geneidy, “Validating Walkability Indices: How Do Different Households Respond to the Walkability of their neighborhoods? *Transportation Research Part D*, 16 (2011), 309-315.

Marion, B. and M. Horner, “Comparison of Socioeconomic and Demographic Profiles of Extreme Commuters in Several U.S. Metropolitan Statistical Areas,” *Transportation Research Record*, 2013 (2007), 38-45.

Mast, M., M. Sieverdin, M. Esslen, K. Graber, L. Jancke,“Masculinity Causes Speeding In Young Men,” *Accident Analysis and Prevention*, 40 (2008), 840-842.

Mokhtarian, Patricia and Xinyu (Jason) Cao, “Examining the Impacts of Residential Self-Selection on Travel Behavior: A focus on methodologies,” *Transportation Research Part B*, 42 (2008), 204-228.

Myers, D, “Changes over Time in Transportation Mode for the Journey to Work: Aging and Immigration Effects,” Conference on Decennial Census Data for Transportation Planning, Irvine CA, 1996.

National Academies of Science (NAS), *Federal Funding of Transportation Improvement in*

BRAC Cases. Special Report 302,Sussman, J., Black, T, Deen, T., Gosnell, J., Inman, M., Johnson, A., Meurer, F., Neels, K., Schoener, G., and R. Yim. Transportation Research Board of the National Academies, 2011.

Neog, D., “Evaluating the Effect of the Workplace Built Environment on Travel Behavior of Employees in Southeast Florida,” Dissertation submitted to Florida State University, 2009.

Ozkan, T., and T. Lajunen,“Why Are Young Men Risky Drivers? The Effects of Sex and Gender-Role on Aggressive Driving, Traffic Offences and Accident Involvement Among Young Men and Women Turkish Drivers,” *Aggressive Behavior*, 31 (2006), 547–558.

Parry, I., M. Walls, and H. Harrington, “Automobile Externalities and Policies,” *Journal of Economic Literature*, 45 (2007), 373–399.

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.

Shoup, Donald C., “Evaluating the Effects of Cashing Out Employer-Paid Parking: Eight Case Studies,” *Transport Policy*, 4 (1997), 201–216.

Segal, Mady W., “The Military and the Family as Greedy Institutions,” *Armed Forces and Society*, 13 (1986), 9-38.

Small, Kenneth and C. Kazimi, “On the Costs of Air Pollution from Motor Vehicles,” *Journal of Transport Economic Policy*, 29 (1995), 7-32.

Stradling, S.G., M.L. Meadows, S. Beatty, “Helping Drivers Out of Their Cars: Integrating Transport Policy and Social Psychology for Sustainable Change.” *Transport Policy*, 7 (2000), 207-215.

Steg, L., C. Vlek, G. Slotegraaf, “Instrumental-Reasoned and Symbolic-Affective Motives for using a Motor Car,” *Transportation Research Part F*, 4 (2001), 151-169.

Steg, L,. “Car Use: Lust and Must. Instrumental, Symbolic and Affective Motives for Car Use,” Transportation Research Part A, 39 (2005), 147-162.

Steiner, R. L., “Residential Density and Travel Patterns: Review of the Literature,” *Transportation Research Record*, 1466 (1994), 37– 43.

Sussman, J., T. Black, T. Deen, J. Gosnell, M. Inman, A. Johnson, F. Meurer, K. Neels, G. Schoener and R. Yim, “Federal Funding of Transportation Improvement in BRAC Cases,” Special Report 302, 2011, Transportation Research Board of the National Academies.

Tal, G. and S. Handy, “Travel Behavior of Immigrants: An Analysis of the 2001 National Household Travel Survey,” *Transport Policy*, 17 (2010), 85-93.

U.S. Army. 1972. “U.S. Army in World War II, The Technical Services, The Corps of Engineers: Construction in the U.S.” (Office of the Chief Military History United States Army: Washington DC).

Zhang, Ming, “The Role of Land Use in Travel Mode Choice – Evidence from Boston and Hong Kong,” *Journal of American Planning Association*, 70 (2004), 344-360.

Zhou, B., K. Kockelman, “Self-Selection in Home Choice: Use of Treatment Effects in Evaluating the Relationship between the Built Environment and Travel Behavior,” *Transportation Research Record*, 2077 (2008), 54-61.

APPENDIX I

TABLE 10: Two Sample t-Tests of Veteran and Civilian Worker Populations socio-demographic, economic and birthplace variables (2007-2009 ACS)

	Civilian Workers n = 2,512,200				Veteran Workers n = 251,391				
	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Sig
Commute									
Drive to Work Frequency	0	1	0.89	0.31	0	1	0.92	0.27	****
Drive Alone to Work Frequency	0	1	0.80	0.30	0	1	0.87	0.23	****
Socio-economic / Demographic									
Age (years)	17	61	39.39	12.19	17	61	48.43	10.28	****
Family income ($10,000)	-3.1	137	6.65	6.06	-2.4	137	10.71	53.7	****
Education level (years)	4	21	13.50	2.54	4	21	13.61	2.02	*
Female (dummy)	0	1	0.47	0.50	0	1	0.10	0.29	****
Race American Indian (dummy)	0	1	0.01	0.10	0	1	0.01	0.11	
Race White (dummy)	0	1	0.79	0.38	0	1	0.85	0.36	****
Race Black (dummy)	0	1	0.11	0.28	0	1	0.11	0.31	**
Race Pacific Islander (dummy)	0	1	0.002	0.05	0	1	0.003	0.05	*
Race Asian (dummy)	0	1	0.04	0.22	0	1	0.02	0.13	**
Race Other (dummy)	0	1	0.04	0.20	0	1	0.02	0.14	****
Born in Northeast Region (dummy)	0	1	0.12	0.31	0	1	0.11	0.31	****
Born in Mid-Atlantic Region (dummy)	0	1	0.13	0.12	0	1	0.14	0.35	
Born in East North Central Region (dummy)	0	1	0.20	0.23	0	1	0.26	0.44	**
Born in West North Central Region (dummy)	0	1	0.03	0.15	0	1	0.03	0.17	
Born in Southern Atlantic Region (dummy)	0	1	0.09	0.27	0	1	0.09	0.29	****
Born in East South Coast Region (dummy)	0	1	0.08	0.26	0	1	0.09	0.29	**
Born in South Coast West Region (dummy)	0	1	0.08	0.26	0	1	0.08	0.27	***
Born in US Mountain West states (dummy)	0	1	0.03	0.17	0	1	0.03	0.17	*
Born in US Pacific states (dummy)	0	1	0.12	0.31	0	1	0.11	0.31	****
Born in Latin America (dummy)	0	1	0.08	0.15	0	1	0.01	0.12	****
Born in West. Europe / Scandinavia (dummy)	0	1	0.01	0.10	0	1	0.01	0.11	****
Born in East Asian countries (dummy)	0	1	0.03	0.17	0		0.01	0.10	**
Immigration									
Immigrated to US 0-5 years ago (dummy)	0	1	0.02	0.13	0	1	0.001	0.03	****
Immigrated to US 5-10 years ago (dummy)	0	1	0.02	0.15	0	1	0.001	0.04	****
Immigrated to US >10 years ago (dummy)	0	1	0.08	0.30	0	1	0.05	0.21	****
Family									
Hours worked per week (hours)	1	99	39.90	11.89	0	99	43.46	10.78	***
Female worker with kids (dummy)	0	1	0.10	0.31	0	1	0.03	0.16	****
Family size (number)	1	31	2.69	1.49	1	16	2.47	1.29	****
Lifecycle: adult no kids (dummy)	0	1	0.60	0.49	0	1	0.63	0.48	****
Lifecycle: adult with kid(s) (dummy)	0	1	0.07	0.25	0	1	0.04	0.20	****
Lifecycle: 2 adults with kids (dummy)	0	1	0.32	0.47	0	1	0.32	0.47	
Number of kids (number)	0	9	0.56	0.93	0	8	0.53	0.88	****

TABLE 11: Two Sample t-Tests of Veteran and Civilian Worker Populations Built Environment Variables (2007-2009 ACS)

	Civilian Workers n = 2,512,200				Veteran Workers n = 251,391				
Variable	Min	Max	Mean	Std Dev.	Min	Max	Mean	Std Dev.	Sig
Residential PUMA									
Worker density (workers/sq. km)	0.2	156,495	1,755	6399.0	1.56	29,374	955.9	3698	****
Renter density (renters/sq. km)	0.009	43,317	572.9	1872.6	0.009	43,317	256.6	1077.3	****
Bus density (bus workers/sq. km)	0	317	7.1	19.81	0.004	169	2.55	7.03	****
Subway density (subway workers/sq. km)	0	25	0.29	1.56	0	25	0.10	0.31	****
Lives in city center (dummy)	0	1	0.15	0.36	0	1	0.22	0.42	****
Lives in rural area (dummy)	0	1	0.16	0.34	0	1	0.13	0.4	****
Lives in suburban area (dummy)	0	1	0.35	0.44	0	1	0.33	0.47	*
Lives in metropolitan area, land use type not specified (dummy)	0	1	0.34	0.47	0	1	0.44	0.48	
Workplace PUMA									
Worker density (workers/sq. km)	0.2	156,495	3,360	15,135	0.2	156,495	1898.5	9768.6	****
Renter density (renters/sq. km)	0.005	30,074	421.3	2,512	0.005	30,074	191.0	1516.2	****
Bus density (bus workers/sq. km)	0	317	10.4	33.67	0	317	6.2	22.59	****
Subway density (subway workers/sq. km)	0	25	0.52	2.67	0	25	0.26	1.76	****