Driving in Force: The Influence of Workplace Peers on Commuting Decisions on U.S. Military Bases[1]

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Abstract

We investigate the role of social influence in the commute to work. Using instruments to address the endogeneity of commute decisions and a dataset of U.S. military commuters on 100 military bases over the period 2006 to 2013, we show that workplace peers positively influence one another's decisions to drive alone to work and carpool to work. All else equal, an increase in the fraction of peers who drive alone of 10 percentage points increases the probability of driving alone by 6.05 percentage points. An increase in the fraction of peers who carpool of 10 percentage points increases the probability of carpooling by 5.14 percentage points. To examine whether conventional measures of social status and seniority predict who exerts the strongest influence on others, we disaggregate the dataset into subgroups and identify which subgroups have the greatest influence and which are most susceptible to influence. Results show that in commute decisions, intra-group influence can be more important than inter-group influence. This suggests that workplace travel interventions that seek to shift employees away from driving alone or toward carpooling may be most effective if communicated by one's own peer group.

Keywords: peer influence, military, mode choice, commute, travel behavior, Department of Defense

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1. Introduction

Social influence has been shown to play an important role in behavior at the individual-level, including behavior related to consumption (e.g., Goolsbee and Klenow, 2002), income and labor (e.g., Topa, 2001), education (e.g., Angrist and Lang, 2004), health (e.g., Trogdon, Nonnemaker and Pais, 2008; Ma, Lin Lawell and Rozelle, 2015), and crime (e.g., Glaeser, Sacerdote and Scheinkman, 1996). Recently, economists have become interested in the role of social influence in decisions with environmental ramifications such as vehicle purchases (Grinblatt, Keloharju and Ikaheimo, 2008), the adoption of solar panels (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015), energy conservation (Allcott, 2011; Delmas and Lessem, 2014), and the adoption of green products (Kahn and Vaughn, 2009).

Research in social psychology suggests that an individual's motivation to conform to a majority behavior (e.g., driving alone to work) is governed by informational (Mackie, 1987) or normative (Moscovici, 1980) forces. For example, according to Mackie's (1987) objective consensus approach, an employee may choose to drive alone to work because driving alone is viewed as the "correct" behavior (i.e. the objective consensus) in a given workplace. On the other hand, Moscovi's (1981) conversion theory suggests that an employee may decide to drive alone after realizing this will help him or her be more liked by workplace peers. Even if a worker does not agree internally with a given majority behavior, he or she may conform to that behavior to avoid rejection or punishment from the group (Cialdini and Trost, 1998).

Norm transmission intensifies when the norms are communicated by individuals of authority or higher social status who may have who have superior information and power through "knowledge, talent, or fortune" (Cialdini and Trost, 1998, p. 170). Norm transmission also intensifies when the norms are communicated by members of one's own social group through social validation, which arises when one looks to other individuals – often those similar to oneself – for confirmation that a given action is acceptable (Cialdini and Trost, 1998).

This paper examines how workplace peers influence one another's mode of travel to work. Specifically, we study how the normative commuting behavior at a given work site affects whether an individual drives alone to work and whether an individual carpools to work. One unique feature of our research is that we disaggregate observations into sub-groups to determine which subgroups have the greatest influence and which groups are most susceptible to influence. The ability of a workplace or jurisdiction to reduce the environmental, economic, or societal burden of commuting begins with understanding the forces behind commuting decisions and how those decisions can be shifted.

We focus in particular on peer effects between military personnel who work on the same military base, for several reasons. First, unlike many workplaces, military bases are limited to a known geographic area and set of workplace peers: that within the base perimeter. Thus, the physical movements of military personnel and the people with whom they interact are arguably better controlled than other workplaces identifiable in U.S. Census data. Second, to examine workplace peer influence requires a sizeable sample from a given workplace. We are not aware of other surveys with commute to work variables in which such a large number of individuals (10,000s in our dataset) can be identified and located at a specific worksite. Third, unlike many workplaces, a military base is a self-contained community. Most bases have an area of dense employment with administrative buildings and operations offices; training grounds for physical fitness or combat exercises; a commercial area with retail shops and restaurants; a warehouse section for the storage of machinery, tools, and vehicles; and residential communities in the form of barracks, ships' berthings, and base housing (U.S. DoD, 2015). Thus, as the military operates as a community, peer effects may be important.

We build on previous studies of peer effects between U.S. military members in other contexts. Carrell, Fullerton and West (2009) exploit random assignment of individuals to roommates and squadrons at the U.S. Air Force Academy to estimate how one's cohort influences academic achievement. Lyle and Smith (2014) examine the influence of high-performing senior officers on junior officers in the U.S. Army.

This paper also draws on the extensive literature on transportation mode choice (e.g., McFadden, 1974; Chatman, 2003; Bento et al., 2005; Belz and Lee, 2012). Most research in this field uses the characteristics of the individual and the physical environment (or "built environment") as key explanatory variables, often in a discrete choice framework. In this paper we also use a discrete choice model and control for individual built environment variables. To estimate the influence of "peers," we use the average rates of driving alone (versus other modes) and carpooling[2] (versus other modes) at the same workplace as additional (endogenous) explanatory variables.

A weakness of econometric analyses of travel decisions is that they often rely on cross-sectional datasets – like the National Household Travel Survey (U.S. DOT, 2009) 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) from the Integrated Public Use Microdata Series (IPUMS) – is a

[2] "Carpooling" is often referred to as "ridesharing" in the transportation literature.

repeated cross-section dataset that includes variation across both individuals[3] and time, and is suitable to our needs because it includes several variables on the commute to work.

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, some of which may be correlated with the commute decisions of peers.[4] Lastly, there is a group self-selection problem because individuals may choose careers, workplace locations, and housing locations based on similar attitudes which may carry over to commuting preferences.

This paper addresses these endogeneity problems using instrumental variables. In particular, we instrument for the fraction of base workers who drive alone with the fraction of base workers who are born in Latin America, and we instrument for the fraction of base workers who carpool with the fraction of base workers who immigrated to the United States 5-10 years ago. Latin American-born individuals drive alone at lower rates than the general population in the U.S. (e.g., McKenzie, 2015) and immigrants carpool at higher rates than the general population (e.g., Myers, 1997; Blumenberg and Smart, 2014; McKenzie, 2015). 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

[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. PUMAs are the smallest identifiable geographic region in census data at the person-level and typically have ~100,000 people.

[4] Examples of unobservables that are difficult to quantify but could affect the commute decisions of both an individual and his/her workplace peers include the availability of pedestrian walkways at the workplace or distance from parking to office buildings.

driving alone or carpooling on a base, but are unrelated to whether a given individual chooses to drive alone or carpool (Brock and Durlauf, 2001; Brock and Durlauf, 2002; Walker et al., 2011).

Our results show that workplace peers positively influence one another's decisions to drive alone to work and carpool to work. An increase in the fraction of peers who drive alone of 10 percentage points increases the probability of driving alone by 6.05 percentage points. An increase in the fraction of peers who carpool of 10 percentage points increases the probability of carpooling by 5.14 percentage points. We also find that intra-group influence can be more important than inter-group influence. This suggests that workplace travel interventions that seek to shift employees away from driving alone or toward carpooling may be most effective if communicated by one's own peer group.

The balance of this paper proceeds as follows. We present our data in Section 2. We describe our econometric model in Section 3. We present our results in Section 4. Section 5 concludes.

2. Data

Our main dataset – the American Community Survey (ACS) – is available for download from the IPUMS-USA website maintained by the University of Minnesota Population Center (Ruggles et al., 2015). 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. We use annual data over the period 2006 to 2013. 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. We use person-level weights provided in the ACS as sampling weights[5] to properly account for under-sampled individuals (Ruggles et al., 2015).[6]

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 we are able to reduce the size of the geographic region even further.[7] In our sample of 100 military bases, the average area of PUMAs containing those bases is 7,662 km^2, whereas the average area of the 100 military bases in the sample is 178 km^2.

Each individual in the dataset appears a single time and reports a single commute mode choice decision. The decision to drive alone to work versus taking other modes (carpool, bus, train, ferry, taxi, walk, cycle, worked at home, other) was made by 86% of military members in 2013. The decision to carpool to work versus taking other modes (drive alone, bus, train, ferry, taxi, walk, cycle, worked at home, other) was made by 7% of military members in 2013.[8]

We control for individual-level variables as well as built environment variables. The built environment variables control for differences in land-use and spatial patterns across individuals. While built environment 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).[9]

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[5] Sampling weights indicate the inverse probability that an observation was sampled.
[6] We also run a specification in which we do not weight observations for robustness.
[7] Active duty military, veterans, and civilians are identified with the census variable "vetstat" which defines individuals as active, veteran, or civilian. In our base case sample, we omit military personnel who live in barracks, on ships, in hospitals or in military prisons, focusing instead on military members who live offbase in private houses or apartments and commute daily to base. For robustness, we also run a specification of our military peer effects model that includes all military personnel.
[8] If respondents took more than one mode to work (e.g. car, train), the survey instructs them to mark the mode in which they travelled the greatest distance.
[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.

We also control for the log average gasoline price by year and state (U.S. DOE, 2015) to help control for differences in driving expenses. We include base fixed effects to control for structural differences between bases in travel behavior as well as year effects to control for common shocks.

We demonstrate how military commuters differ from civilian commuters in Appendix A. To do this, we compare distributions of each control variable for three commuter groups in the U.S.: military, veterans, and civilians. The veteran group is included because they are still linked to the military (via their prior career) but are no longer influenced by the same built environment variables or workplace social influence variables.[10] We find that a higher percentage of military personnel drive alone to work than civilians, and a lower percentage of military personnel carpool than civilians. We then estimate a discrete choice model using data on all U.S. commuters (and dummy variables for military members and veterans) to understand whether being in the military or a veteran has an effect on the probability of driving or driving alone when controlling for socio-economic, demographic, and built environment variables. We find that being in the military increases the probability of driving alone by 1.4 to 7.5 percentage points and decreases the probability of carpooling by 1 to 4 percentage points relative to civilians. Being a veteran increases the probability of driving alone by 7.9 to 11.7 percentage points and decreases the probability of carpooling by 0.03 to 2 percentage points relative to civilians.

We use a military-only subsample to examine whether an individual's decision to drive alone or carpool to work is influenced by the decisions of his or her workplace peers to drive

[10] However, it is likely that some self-selection still occurs since veterans often still live in cities with military bases (Ruggles et al., 2015).

alone or carpool. Our sample is from bases for which we have 100 or more observations.[11] Table 1 lists the 100 military bases in our sample and the percent of commuters who drive alone and carpool on each. Summary statistics of the variables in our data set, along with results of two-sample t-tests comparing the military with civilians, are in Tables A1 and A2 in Appendix A.

3. Econometric Model

To analyze the effects of peers on the decisions to drive alone and carpool, we estimate a multinomial logit model of the commute choice decision a_{it}, where $a_{it} = 1$ indicates that individual *i* drove alone to work in year *t*, $a_{it} = 2$ indicates that individual *i* carpooled to work in year *t*, and $a_{it} = 0$ indicates that individual *i* did not drive to work in year *t*. We include as endogenous regressors n_{it} the fraction of base workers who drive alone and the fraction of base workers who carpool, and we use instruments to address the endogeneity of these endogenous regressors. We also include as regressors control variables x_{it} which have been shown to predict commute decisions (Bento et al., 2005), as well as base fixed effects and year effects, and we cluster standard errors at the base level. The multinomial logit model is given by:

$$\Pr(a_{it} = j) = \frac{\exp(n'_{it}\beta_j + x'_{it}\gamma_j)}{\sum_{\tilde{j}=0}^{2}\exp(n'_{it}\beta_{\tilde{j}} + x'_{it}\gamma_{\tilde{j}})}, \tag{1}$$

where $\Pr(\cdot)$ denotes probability.

[11] 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, 100 bases fit our selection criteria.

The parameters of interest are β_j , the coefficients corresponding to commute choice j on the endogenous variables n_{it} : the fraction of base workers who drive alone and the fraction of base workers who carpool. To address the endogeneity of these variables in a multinomial logit model, we use the two-stage residual inclusion (2SRI) estimation method developed by Terza, Basu and Rathouz (2008) and applied by Grabowski et al. (2013). In the first stage, we run first stage regressions of the endogenous variables on instruments and the exogenous regressors. In the second stage, we include the residuals from the first-stage regressions as regressors in the multinomial logit regression.

We instrument for the fraction of base workers who drive alone with the fraction of base workers who are born in Latin America, and we instrument for the fraction of base workers who carpool with the fraction of base workers who immigrated to the United States 5-10 years ago. These variables were found to be significant determinants of the drive alone and carpool decisions, respectively, in the general population multinomial logit model in Table A5 in Appendix A. Past travel research likewise demonstrates that Latin American-born individuals drive alone at lower rates than the general population in the U.S. (e.g., McKenzie, 2015) and that immigrants carpool at higher rates than the general population (e.g., Myers, 1997; Blumenberg and Smart, 2014; McKenzie, 2015). 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 alone or carpooling on a base, but are unrelated to whether a given individual chooses to drive alone or carpool (Brock and Durlauf, 2001; Brock and Durlauf, 2002; Walker et al., 2011).

Table 2 presents the results of the first-stage regressions of the fraction of base workers who drive alone and of the fraction of base workers who carpool. The instruments in both first-stage regressions are significant at the 0.1% level and both first-stage F-statistics are greater than 12.

To examine if the instruments are correlated with unobserved built environment factors that may affect commute decisions and therefore whether the exclusion restriction is satisfied, we run a falsification test of the first-stage regression in which we use as dependent variables pseudo-endogenous variables rather than our actual endogenous variables. In particular, instead of the fraction of military personnel on base who drive alone, we use the following pseudo-endogenous variable: the fraction of non-military people in the PUMA who drive alone. Likewise, instead of the fraction of military personnel on base who carpool, we use the following pseudo-endogenous variable: the fraction of non-military people in the PUMA who carpool. If the exclusion restriction is satisfied and the instruments for the commute decisions of military peers on the base are not correlated with unobserved built environment factors that affect individual commute decisions, then we would expect that our instruments – the fraction of military personnel on base who are born in Latin America and the fraction of military personnel on base who immigrated to the United States 5-10 years ago – should not be strong predictors of the fraction of non-military people in the PUMA who drive alone and the fraction of non-military people in the PUMA who carpool, respectively. In other words, if the exclusion restriction is satisfied, characteristics of military workers we use as instruments should not explain the commute behavior of those not in the military.

We present the results of our falsification test of the first-stage regressions in Table 3. The instruments are not significant at a 5% level and the first-stage F-statistics are 2.11 and 0.30. The characteristics of military workers we use as instruments therefore do not explain the commute behavior of those not in the military. Thus, the instruments are not correlated with unobserved built environment factors that affect commute decisions and the exclusion restriction is satisfied.

To provide further evidence that the instruments are not correlated with unobserved built environment factors that affect commute decisions and that the exclusion restriction is satisfied, we examine how correlated the instruments are with observed built environment and state-level variables. As seen in Table 4, neither instrument is highly correlated with any of the built environment and state-level variables; all the correlations are lower than 0.33. Thus, the instruments are not correlated with unobserved built environment factors that affect commute decisions and the exclusion restriction is satisfied.

4. Results

4.1 Peer Effects

Table 5 presents the results of the two-stage residual inclusion (2SRI) estimation of the multinomial commute choice model. Marginal effects at the mean values of the covariates are reported. The fraction of peers who drive alone has a significant positive effect on the decision to drive alone; an increase in the fraction of peers who drive alone of 10 percentage points increases the probability of driving alone by 6.05 percentage points.[12] Similarly, the fraction of peers who carpool has a significant positive effect on the decision to carpool; an increase in the fraction of peers who carpool of 10 percentage points increases the probability of carpooling by 5.14 percentage points.

We also present a few alternative specifications in Table B1 in the Appendix B. In specification (2), we do not weight our observations. In specification (3), we estimate the

[12] This means, for example, that if the probability of driving alone is 50% when 40% of one's peers drive alone, then if 50% of one's peers drive alone (instead of 40%), the probability of driving alone increases to 56.04%.

multinomial logit model without using instruments to address the endogeneity of the peer effect variables. In specification (4), we include all members of the military, including those who live in barracks, on ships, in hospitals, or in military prisons, and who therefore do not commute, as choosing action $a_{it} = 0$ (do not drive).[13] Specification (5) repeats specification (4) without using instruments to address the endogeneity of the peer effect variables. The significant positive effect of the decision of peers to drive alone on an individual's decision to drive alone is robust across all specifications. The significant positive effect of the decision of peers to carpool on an individual's decision to carpool is robust across most specifications.

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 may have a positive feedback.

4.2 Interaction Models

To examine how the magnitude of the peer effect varies with different characteristics of the individual being influenced, we estimate interaction versions of the two-stage residual inclusion multinomial logit military peer effects model in which we interact the endogenous peer effect variables with various individual-level covariates which have been shown in past travel research to be important determinants of travel. These include age, years in military, income, whether the individual lives in an urban environment, number of children, and hours worked per week.

The interaction models are identical to the two-stage residual inclusion multinomial logit military peer effects model in Table 5 except we include interactions of the endogenous peer

[13] In our base case sample, we omit military personnel who live in barracks, on ships, in hospitals or in military prisons, focusing instead on military members who live offbase in private houses or apartments and commute daily to base.

effect variables with the relevant characteristic of the individual (e.g. fraction of workers who drive * individual *i*'s income).[14] We instrument for the endogenous variables and their interactions with the same instruments as before, as well as with the instruments interacted with the respective individual-level characteristic. A significant coefficient on the endogenous interaction variable indicates that the strength of the peer effect changes with the relevant individual-level characteristic. For each model, we 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.

The results of the interaction models are presented in Tables 6a and 6b. For the drive alone decision, the effect of the fraction of peers who drive alone on an individual's decision to drive alone increases with the number of children he has. For the carpool decision, the effect of the fraction of peers who carpool on an individual's decision to carpool decreases with the individual's income and number of children. Thus, the results are quite intuitive: the more money an individual makes and the more children he has, the less influenced he is in his carpooling decision by whether his peers carpool.

4.3 Who Are The Strongest "Influencers?"

To examine whether conventional measures of social status and seniority predict who exerts the strongest influence on others, we break our sample into several sub-groups to examine which types of individuals have the greatest influence and which are most susceptible to influence. We use three variables associated with social status (*income, education*, and *age*), one variable related to workplace seniority (*years in the military*), and *gender*. For *income, education*, and *age*, we divide individuals on each military base into two groups based on

[14] Each model also includes the non-interacted endogenous peer effect variables.

whether they are above or below the mean value of the respective variable. For example, the high income sub-group is composed of individuals whose average family income is more than the mean income of $58,700 per year. For *years in the military*, since we only have data on whether the military member was in the military fewer than two years or more than two years, we designate those in the military fewer than two years as more junior, and those in the military more than two years as more senior. For *gender*, we divide individuals into whether they are male or female. Table 7 presents summary statistics of the fraction who drive alone and the fraction who carpool for each sub-group.

Tables 8a-e show the results of two-stage residual inclusion multinomial logit military peer effects models in which the peer effects are broken down by the type of group exerting influence. In particular, Tables 8a-e present peer effects by income of peers, by education of peers, by age of peers, by seniority of peers, and by gender of peers, respectively. We also present results of tests that both groups of peers have the same effect. For example, in the model of peer effects by income of peers, we test whether the coefficient on the fraction of peers in the high income group who drive alone is the same as the coefficient on the fraction of peers in the low income group who drive alone; and we test whether the coefficient on the fraction of peers in the high income group who carpool is the same as the coefficient on the fraction of peers in the low income group who carpool.

According to our results in Tables 8a-e, military personnel are more likely to drive alone if peers who are younger and more junior drive alone. The drive alone decision of younger peers has a more positive effect on an individual's drive alone decision than that of older peers, and the difference is statistically significant. According to our results, military personnel are more likely to carpool if peers who have higher income and higher education, and who are younger, more senior, and male carpool.

Tables 9a-e show the results of two-stage residual inclusion multinomial logit military peer effects models in which the peer effects are broken down by both the type of the group exerting influence and the type of the individual being influenced. In particular, Tables 9a-e present peer effects by the income of the individual and income of the peers; by the education of the individual and education of the peers; by the age of the individual and age of the peers; by the seniority of the individual and seniority of the peers; and by the gender of the individual and gender of the peers, respectively.

In Tables 9a-e, we also present results of tests of whether a particular group of peers has the same effect on different types of individuals. For example, in the model of peer effects by income and income of peers, we test whether the effect of the fraction of peers in the high income group who drive alone on an individual's decision to drive alone is the same for high income individuals and low income individuals; and whether the effect of the fraction of peers in the low income group who drive alone on an individual's decision to drive alone is the same for high income individuals and low income individuals.

According to the results by income and income of peers in Table 9a, the drive alone decision of lower income peers has a significantly larger effect on the driving alone decisions of lower income individuals than on that of higher income individuals, perhaps because higher income individuals are less influenced by lower income individuals. The carpooling decision of higher income peers has a significantly larger effect on the carpooling decisions of higher income individuals than of lower income individuals, perhaps because higher income individuals are more likely to carpool with higher income individuals. Similarly, the carpooling decision of lower income peers has a significantly larger effect on the carpooling decisions of lower income individuals than of higher income individuals, perhaps because lower income individuals are more likely to carpool with lower income individuals.

According to the results by education and education of peers in Table 9b, we cannot reject the equality of the effects of peers on higher education and lower education individuals.

According to the results by age and age of peers in Table 9c, the drive alone decision of older peers has a significantly more negative effect on the driving alone decisions of older individuals than on that of younger individuals. The drive alone decision of younger peers has a significantly larger effect on the driving alone decisions of younger individuals than on that of older individuals, perhaps because younger peers have more of an influence on younger individuals than on older individuals. The carpooling decision of younger peers has a significantly larger effect on the carpooling decisions of younger individuals than of older individuals, perhaps because younger individuals are more likely to carpool with younger individuals.

According to the results by seniority and seniority peers in Table 9d, the drive alone decision of more senior peers has a significantly more negative effect on the driving alone decisions of more junior individuals than on that of more senior individuals, indicating that more junior individuals are less likely to drive alone if more senior peers drive alone. The drive alone decision of more junior peers has a significantly larger effect on the driving alone decisions of more junior individuals than on that of more senior individuals, perhaps because more junior peers have more of an influence on more junior individuals than on more senior individuals. The carpooling decision of more senior peers has a significantly larger effect on the carpooling decisions of more senior individuals than of more junior individuals, perhaps because more senior individuals are more likely to carpool with more senior individuals.

According to the results by gender and gender of peers in Table 9e, the drive alone decision of female peers has a significantly positive effect on the drive alone decision of females but a significantly negative effect on the drive alone decision of males. The drive alone decisions of male peers has a significantly positive effect on the drive alone decision of males but no significant effect on the drive alone decision of females. Thus, individuals are more influenced by the drive alone decisions of peers of their same gender in their decision to drive alone. The carpooling decision of female peers has a significantly larger effect on the carpooling decision of females than of males, perhaps because females are more likely to carpool with females. Similarly, the carpooling decision of male peers has a significantly larger effect on the carpooling decision of males than of females, perhaps because males are more likely to carpool with males.

5. Conclusion

As seen in Table A1 of Appendix A, over the period 2006 to 2013, military personnel spent an average of over 50 hours a week at work. It is not surprising, then, that workers at the same military base may influence one another's commute decisions. Using instruments to address the endogeneity of the decisions of one's workplace peers, we find that military workers are positively influenced by their peers in both the decision to drive alone to work and the decision to carpool to work. An increase in the fraction of peers who drive alone of 10 percentage points increases the probability of driving alone by 6.05 percentage points. An increase in the fraction of peers who carpool of 10 percentage points increases the probability of carpooling by 5.14 percentage points.

We find that the more children an individual has, the more he is influenced by whether his peers drive alone in his decision to drive alone. The more money an individual makes and the more children he has, the less influenced he is by whether his peers carpool in his carpooling decision.

We also explore whether conventional measures of social status and seniority predict who exerts the strongest influence on others. In the driving alone decision, individuals of lower social status or seniority have more of an influence on peers who are also of lower social status or seniority than on individuals of higher social status or seniority. Individuals are more influenced by the drive alone decisions of peers of their same gender in their decision to drive alone. In the carpooling decision, individuals of the same level of social status, seniority, or gender exert the strongest influence on each other, probably because individuals are more likely to carpool with peers of the same level of social status, seniority, or gender.

We therefore find that intra-group influences are stronger than inter-group influence. This suggests that, for carpooling decisions and, to a somewhat lesser extent, for the decision to drive alone, social validation is a stronger motivator towards conformity than authority.

There are two possible mechanisms that could explain why intra-group influences are stronger than inter-group 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., 2003). Second, according to Festinger's (1954) Theory of Social Comparison, when objective evidence is not present, we use similar others for the basis of comparison. It follows that – at least in some domains – norm transmission occurs most strongly within similar social groups than from higher status to lower status groups.

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 may have a positive feedback.

The practical implications of this work revolve around workplace commute programs. In the past 30 years, a number of innovative 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 are 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, Newson and Davis., 2010). Cairns, Newon and Davis (2010) show that reductions in driving of up to 18% have been observed in well-organized commute programs in the UK. Our research suggests that once these programs shift the norms at a workplace towards non-auto modes or carpooling, there will be a positive feedback because of peer effects. The research also suggests that using one's own peer group to convey a message about the "correct" mode of travel could be more effective than relying on a message from those people of a higher or different social or positional status.

Our results should be interpreted with caution for at least two reasons. First, our analysis consists of a military-only sub-sample, which was shown in Appendix A to differ along several important socio-economic, demographic, and travel-related boundaries. The military places an emphasis on conforming in a way other workplaces may not (Katzenstein and Reppy, 1999). Thus, we suspect our measured peer effects to be somewhat higher than those in an average workplace. Second, this paper considers the influence of the normative commute behavior of an entire military base. As seen in Table 1, some military bases are quite large, both in personnel and/or in geographic area. The influence of an entire base's normative behavior versus that of a more immediate group (i.e. only those in their battalion, squadron, etc.) would be interesting to examine in future work.

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Table 1: Military Bases in Sample

Base Name	Service	State	# Observations 2006-2013	# Workers on Base in 2010	Percent of commuters who: Drive Alone	Carpool
Maxwell-Gunter	Army	AL	271	9,502	84%	6%
Fort Rucker	Army	AL	281	7,428	91%	7%
Greely Wainwright	Army	AK	393	7,763	79%	17%
Little Rock Air Force Base	AF	AR	274	7,257	86%	12%
Davis-Monthan Air Force Base	AF	AZ	417	7,457	89%	7%
Luke Air Force Base	AF	AZ	512	5,386	87%	8%
Fort Huachuca	Army	AZ	374	8,907	79%	12%
MC Air Station Yuma	MC	AZ	323	4,049	74%	11%
Pendleton SDMCTC	MC	CA	5,024	52,497	82%	10%
Naval Air Station Lemoore	Navy	CA	297	4350	81%	11%
29 Palms	MC	CA	815	12,075	78%	13%
Mugu-Hueneme	Navy	CA	270	8,977	79%	8%
Beale Air Force Base	AF	CA	163	4,403	85%	7%
Edwards Air Force Base	AF	CA	182	5,196	81%	13%
Travis Air Force Base	AF	CA	332	7,676	87%	9%
Vandenberg Air Force Base	AF	CA	171	3,838	85%	7%
Camp Roberts	Army	CA	445	331	64%	16%
Buckley Air Force Base	AF	CO	213	3,993	78%	11%
Fort Carson	Army	CO	1,534	20,183	89%	7%
Navy Subase New London	Navy	CT	404	9,433	81%	9%
Dover Air Force Base	AF	DE	210	4,060	89%	7%
Jacksonvill Mayport	Navy	FL	836	23,000	88%	6%
NAS Key West	Navy	FL	252	1,604	77%	11%
Naval Air Station Pensacola	Navy	FL	694	14,656	84%	10%
Eglin AFB	AF	FL	756	10,308	90%	7%
MacDill Air Force Base	AF	FL	391	7,125	84%	10%

Patrick Air Force Base	AF	FL	115	2,715	92%	5%
Tyndall Air Force Base	AF	FL	346	4,657	86%	8%
Naval Submarine Base Kings Bay	Navy	GA	251	5,637	92%	5%
Fort McPherson	Army	GA	145	2,093	89%	7%
Moody Air Force Base	AF	GA	235	4,912	87%	9%
Robins Air Force Base	AF	GA	281	18,206	88%	9%
Fort Benning	Army	GA	587	31,698	88%	9%
Fort Gordon	Army	GA	589	16,160	88%	7%
Fort Stewart	Army	GA	577	18,447	86%	11%
Hunter Army Airfield	Army	GA	194	5,979	89%	7%
Kaneohe MCB	MC	HI	3,104	7,100	80%	10%
Mountain Home Air Force Base	AF	ID	144	4,901	74%	22%
Naval Station Great Lakes	Navy	IL	541	24,361	80%	6%
Scott AFB	Army	IL	319	9,231	92%	6%
McConnell Air Force Base	AF	KS	135	5,018	83%	14%
Fort Leavenworth	Army	KS	208	5,824	79%	6%
Fort Riley	Army	KS	655	16,653	85%	11%
Fort Campbell	Army	KT	1,133	31,809	91%	6%
Fort Knox	Army	KT	423	18,423	88%	6%
New Orleans/NSA New Orleans	Navy	LA	108	3,758	74%	15%
Barksdale Air Force Base	AF	LA	307	5,945	92%	5%
Fort Polk	Army	LA	511	10,319	89%	7%
NAS Patuxent River	Navy	MD	222	8,778	90%	6%
Andrews Air Force Base	AF	MD	376	8,294	90%	8%
Whiteman Air Force Base	AF	MO	204	3,624	84%	15%
Fort Leonard Wood	Army	MO	496	29,500	77%	9%
Aberdeen Proving Ground	Army	MD	120	11,662	90%	3%
Fort Meade	Army	MD	785	16,225	85%	7%
Keesler Air Force Base	AF	MS	387	4,694	91%	4%
NAS Meridian	Navy	MS	111	1,003	90%	5%
Offutt Air Force Base	AF	MS	251	1,631	94%	3%
Nellis Air Force Base	AF	NE	542	7,646	81%	12%

Fort Dix	Army	NV	321	8,674	87%	9%
Cannon Air Force Base	AF	NJ	112	5,029	91%	6%
Holloman Air Force Base	AF	NM	190	2,576	85%	10%
Fort Drum	Army	NM	873	2,844	89%	9%
United States Military Academy	Army	NY	286	19,378	73%	5%
Seymour Johnson Air Force Base	AF	NY	449	8,333	87%	10%
Fort Bragg	Army	NC	1,333	4,731	90%	5%
MCAS Cherry Point	MC	NC	445	55,501	90%	6%
MCB Camp Lejeune	MC	NC	2,285	10,387	84%	11%
Wright-Patterson Air Force Base	AF	NC	254	48,210	92%	6%
Tinker AFB	AF	OH	279	14,434	92%	5%
Fort Sill	Army	OK	555	18,450	82%	10%
Naval Station Newport	Navy	OK	179	19,258	82%	9%
Naval Weapons Station Charleston	Navy	RI	316	6,823	87%	9%
Charleston Air Force Base	AF	SC	284	9,151	91%	5%
Shaw Air Force Base	AF	SC	231	4,317	89%	9%
Fort Jackson	Army	SC	752	5,161	88%	2%
Beaufort Parris Island	MC	SC	537	30,516	80%	11%
Naval Air Station Corpus Christi	Navy	SC	123	6,743	91%	4%
Naval Air Station Ft. Worth	Navy	TX	179	5,091	90%	6%
Dyess Air Force Base	AF	TX	320	5,006	91%	4%
Goodfellow Air Force Base	AF	TX	235	5,427	63%	9%
Fort Sam Houston	Army	TX	1,558	2,013	86%	9%
Laughlin Air Force Base	AF	TX	508	19,735	77%	9%
Sheppard Air Force Base	AF	TX	518	1,813	89%	4%
Fort Bliss	Army	TX	1,257	3,830	87%	8%
Fort Hood	Army	TX	1,756	21,626	89%	8%
Hill Air Force Base	AF	TX	198	55,834	93%	6%
Naval Station Norfolk	Navy	UT	2,017	14,498	86%	8%
Little Creek Oceana	Navy	VA	895	52,101	87%	7%
Portsmith Hospital	Navy	VA	446	22,360	85%	10%
Fort Monroe	Army	VA	390	6,063	88%	9%

Fort Belvoir	Army	VA	376	2,299	78%	11%
Fort Eustis	Army	VA	482	10,972	87%	7%
Fort Myer	Army	VA	820	10,771	43%	16%
Fort Lee	Army	VA	200	2,349	87%	8%
Naval Base Kitsap Bremerton	Navy	VA	529	12,043	73%	14%
Naval Station Everett	Navy	WA	180	21,364	73%	15%
Naval Air Station Whidbey Island	Navy	WA	426	1,930	86%	9%
Fairchild Air Force Base	AF	WA	181	5,499	79%	13%
Fort Lewis	Army	WA	1,243	4,557	86%	11%

Notes: All bases have at least 100 observations. AF = Air Force; MC = Marine Corps.

TABLE 2: First-Stage Regressions

	Dependent variable is fraction of military personnel on base who:	
	Drive Alone	*Carpool*
	(1)	(2)
Instrument		
Fraction of military personnel on base who are born in Latin America	-0.240***	
	(0.068)	
Fraction of military personnel on base who immigrated 5-10 years ago		-1.223***
		(0.349)
Built Environment		
Worker density (million workers/sq. km)	-0.0003	-0.0000
	(0.0002)	(0.0002)
Bus density (1,000 bus workers/sq. km)	0.036	0.017
	(0.052)	(0.042)
Lives in city center (dummy)	-0.001	0.003
	(0.002)	(0.002)
Lives in rural area (dummy)	-0.016	0.009
	(0.008)	(0.006)
Lives in suburban area (dummy)	-0.004**	0.0031*
	(0.002)	(0.0014)
State-level		
Log of state gasoline price ($)	-0.048	0.016
	(0.114)	(0.112)
Base fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Standard errors clustered at base level	Yes	Yes
First Stage F-Statistic	12.62	12.36
Observations	37,475	37,475

Notes: Standard errors clustered at the base level are in parentheses. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

TABLE 3: Falsification Test of the First-Stage Regressions

	Dependent variable is fraction of non-military personnel in PUMA who:	
	Drive Alone	*Carpool*
	(1)	(2)
Instrument		
Fraction of military personnel on base born in Latin America	-0.065	
	(0.045)	
Fraction of military personnel on base who immigrated 5-10 years ago		-0.007
		(0.014)
Control variables	Yes	Yes
Base fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Standard errors clustered at base level	Yes	Yes
First Stage F-Statistic	2.11	0.30
Observations	1,221,583	1,221,583

Notes: Standard errors clustered at the base level are in parentheses. We use the following control variables: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

TABLE 4: Correlation between instruments and built environment and state-level variables

	Instrument	
	Fraction of military personnel on base who:	
	Are born in Latin America	Immigrated 5-10 years ago
Built Environment		
Worker density (million workers/sq. km)	0.1854	0.3306
Bus density (1,000 bus workers/sq. km)	0.1210	0.2257
Lives in city center (dummy)	-0.0335	-0.0768
Lives in rural area (dummy)	-0.1036	-0.1872
Lives in suburban area (dummy)	0.0679	0.2550
State-level		
Log of state gasoline price ($)	0.0169	0.1087

TABLE 5: Two-Stage Residual Inclusion Multinomial Logit Military Peer Effects Model

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
	(1)	
Endogenous Peer Effect Variables		
Fraction of military personnel on base who drive alone	0.605*	0.247
	(0.34)	(0.22)
Fraction of military personnel on base who carpool	-0.20	0.514***
	(0.15)	(0.11)
Socio-economic/Demographic		
Age (yrs)	0.023***	-0.017***
	(0.002)	(0.001)
Age-squared (yrs^2)	-0.00030***	0.00021***
	(0.00003)	(0.00002)
Education (10s of years)	0.0003*	-0.0003**
	(0.0002)	(0.0001)
Female (dummy)	-0.02***	0.034***
	(0.01)	(0.004)
Family		
Log of family income ($10,000)	0.007**	-0.006**
	(0.004)	(0.003)
Hours worked per week (100 hours)	-0.00008	0.00003
	(0.0002)	(0.0001)
Family size (100s of people)	-0.017***	0.005*
	(0.003)	(0.002)
Vehicles per adult in household (number)	0.012***	0.003
	(0.004)	(0.003)
Number of children (100s)	0.017***	-0.003
	(0.004)	(0.003)
Immigration		
Born in Latin America (dummy)	0.009	0.019*
	(0.01)	(0.01)
Immigrated to U.S. 0-5 years ago (dummy)	-0.00	-0.01
	(0.02)	(0.02)
Immigrated to U.S. 5-10 years ago (dummy)	-0.00	-0.00
	(0.02)	(0.01)
Immigrated to U.S. >10 years ago (dummy)	0.012	0.001
	(0.01)	(0.01)
Built Environment		
Workers density (million workers/sq. km)	-0.0008	-0.0008

	(0.0008)	(0.0007)
Bus density (1,000 bus workers/sq. km)	0.012	0.019
	(0.08)	(0.07)
Lives in city center (dummy)	0.000	0.008
	(0.01)	(0.01)
Lives in rural area (dummy)	0.004	0.001
	(0.02)	(0.01)
Lives in suburban area (dummy)	0.005	0.004
	(0.01)	(0.01)
State-level		
Log of state gasoline price ($)	-0.13	0.034
	(0.13)	(0.06)
Residuals		
Residual from Fraction who drive alone 1st stage	-0.02	-0.31
	(0.34)	(0.22)
Residual from Fraction who carpool 1st stage	0.122	0.046
	(0.15)	(0.10)
Base fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Standard errors clustered at base level	Yes	Yes
Observations	37,475	37,475

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered by base are in parentheses. The fraction of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

TABLE 6a: Interaction Models

	Dependent variable is probability of:					
	Driving Alone	*Carpooling*	*Driving Alone*	*Carpooling*	*Driving Alone*	*Carpooling*
Interaction included	Age		Years in military		Log of Income	
	(1)		(2)		(3)	
Coefficient on fraction who drive alone	0.06	1.32***	-0.70	1.00	-2.958	1.1639
	(0.58)	(0.47)	(1.53)	(1.45)	(2.723)	(2.528)
Coefficient on interaction with drive alone	0.003	-0.003	0.046	0.01	-0.197	-0.041
	(0.003)	(0.002)	(0.06)	(0.05)	(0.332)	(0.290)
Coefficient on fraction who carpool	-0.953	0.757*	0.39	-1.03	-1.774	4.638**
	(0.65)	(0.44)	(1.61)	(1.37)	(2.758)	(2.220)
Coefficient on interaction with carpool	0.002	-0.002	1.698	-3.794	0.1284	-0.448*
	(0.02)	(0.02)	(4.40)	(3.84)	(0.327)	(0.271)
Total average effect of fraction who drive alone	0.050	1.32**	-0.541	0.99	-4.140	1.16
	(0.58)	(0.47)	(1.53)	(1.45)	(4.91)	(4.39)
Total average effect of fraction who carpool	-0.919	0.70	2.540	-5.20	0.200	4.60
	(0.89)	(0.54)	(6.71)	(5.83)	(4.83)	(4.02)
Mean value of interacted variable	30.82		1.48		12.4	
Control variables[ǂ]	Yes		Yes		Yes	
Base fixed effects	Yes		Yes		Yes	
Year effects	Yes		Yes		Yes	
Standard errors clustered at base level	Yes		Yes		Yes	
Observations	37,475		14,113		37,475	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is

instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.
ǂ We use the following control variables:
Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago
Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 6b: Interaction Models

	Dependent variable is probability of:					
	Driving Alone	*Carpooling*	*Driving Alone*	*Carpooling*	*Driving Alone*	*Carpooling*
Interaction included	Urban		Number of children		Hours worked	
	(4)		(5)		(6)	
Coefficient on fraction who drive alone	0.5979	0.28	0.8216**	0.3223	1.3747*	-0.176
	(0.568)	(0.34)	(0.414)	(0.273)	(0.808)	(0.600)
Coefficient on interaction with drive alone	0.7089	-0.43	0.0357**	-0.053***	-0.002	0.0000
	(0.723)	(0.44)	(0.017)	(0.013)	(0.001)	(0.001)
Coefficient on fraction who carpool	-0.092	0.446***	-0.559***	0.7031***	-0.914	0.9648**
	(0.149)	(0.11)	(0.210)	(0.131)	(0.629)	(0.440)
Coefficient on interaction with carpool	2.918**	-1.549	-0.021	-0.122**	-0.022*	0.0074
	(1.199)	(0.98)	(0.064)	(0.054)	(0.012)	(0.009)
Total average effect of fraction who drive alone	0.716	0.20	0.8425**	0.32	1.370	-0.10
	(0.57)	(0.35)	(0.41)	(0.27)	(0.80)	(0.60)
Total average effect of fraction who carpool	0.290	0.30	-0.565	0.70**	-1.924	0.90**
	(0.26)	(0.20)	(0.21)	(0.14)	(0.80)	(0.44)
Mean value of interacted variable	0.18		0.75		50.7	
Control variables[ǂ]	Yes		Yes		Yes	
Base fixed effects	Yes		Yes		Yes	
Year effects	Yes		Yes		Yes	
Clustered std errors at base level	Yes		Yes		Yes	
Observations	37,475		37,475		37,475	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

ǂ We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 7: Summary Statistics of Fraction Who Drive Alone and Fraction Who Carpool by Sub-group

		Drive Alone *Fraction of subgroup who drive alone*				Carpool *Fraction of subgroup who carpool*			
Subgroup	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**
All individuals	37,475	0.84	0.36	0	1	0.09	0.29	0	1
Higher Income	18,771	0.85	0.35	0	1	0.08	0.27	0	1
Lower Income	18,704	0.84	0.37	0	1	0.10	0.31	0	1
Higher education	12,306	0.86	0.34	0	1	0.07	0.25	0	1
Lower education	25,169	0.84	0.37	0	1	0.10	0.30	0	1
Higher age	16,443	0.87	0.33	0	1	0.06	0.24	0	1
Lower age	21,032	0.83	0.38	0	1	0.11	0.31	0	1
Senior (> 2 yrs)	1,150	0.68	0.47	0	1	0.14	0.35	0	1
Junior (< 2 yrs)	12,963	0.86	0.35	0	1	0.08	0.28	0	1
Female	5,198	0.82	0.39	0	1	0.08	0.28	0	1
Male	32,277	0.85	0.36	0	1	0.08	0.28	0	1

TABLE 8a: Peer Effects by Income of Peers

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:		
Higher income	0.129	-0.09
	(0.49)	(0.37)
Lower income	0.201	0.310
	(0.28)	(0.29)
p-value for test that both groups have same effect	0.29	0.92
Fraction of the following group on base who carpool:		
Higher income	-0.33***	1.663***
	(1.12)	(0.78)
Lower income	0.712	0.477
	(0.73)	(0.49)
p-value for test that both groups have same effect	0.18	0.37
Control variables‡	Yes	
Base fixed effects	Yes	
Year effects	Yes	
Standard errors clustered at base level	Yes	
Observations	37,475	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

‡ We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 8b: Peer Effects by Education of Peers

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:		
Higher education	0.2919	0.5554
	(1.21)	(0.66)
Lower education	-0.692	0.5058
	(1.22)	(1.25)
p-value for test that both groups have same effect	0.41	0.11
Fraction of the following group on base who carpool:		
Higher education	-0.234	0.5623***
	(0.26)	(0.21)
Lower education	0.5080	0.9456
	(0.89)	(0.61)
p-value for test that both groups have same effect	0.53	0.09
Control variables[ǂ]	Yes	
Base fixed effects	Yes	
Year effects	Yes	
Standard errors clustered at base level	Yes	
Observations	37,475	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 8c: Peer Effects by Age of Peers

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:		
Higher age	-0.53	0.218
	(0.36)	(0.35)
Lower age	0.828***	-0.46***
	(0.20)	(0.14)
p-value for test that both groups have same effect	0.02*	0.09
Fraction of the following group on base who carpool:		
Higher age	0.112***	-0.13***
	(0.24)	(0.24)
Lower age	-2.50	-0.24
	(1.97)	(1.17)
p-value for test that both groups have same effect	0.52	0.11
Control variables[ǂ]	Yes	
Base fixed effects	Yes	
Year effects	Yes	
Standard errors clustered at base level	Yes	
Observations	37,475	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 8d: Peer Effects by Seniority of Peers

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:		
More senior	-0.920	-0.831
	(1.73)	(1.32)
More junior	0.1763***	-0.060*
	(0.04)	(0.03)
p-value for test that both groups have same effect	0.11	0.86
Fraction of the following group on base who carpool:		
More senior	-0.253	0.526***
	(0.24)	(0.14)
More junior	0.153*	0.0652
	(0.09)	(0.07)
p-value for test that both groups have same effect	0.09	0.17
Control variables[ǂ]	Yes	
Base fixed effects	Yes	
Year effects	Yes	
Standard errors clustered at base level	Yes	
Observations	13,164	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 8e: Peer Effects by Gender of Peers

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:		
Female	1.633	-1.04
	(1.18)	(1.01)
Male	0.593	-0.453
	(0.966)	(0.88)
p-value for test that both groups have same effect	0.65	0.94
Fraction of the following group on base who carpool:		
Female	-0.301	0.313
	(0.28)	(0.32)
Male	-0.087	0.857***
	(0.39)	(0.24)
p-value for test that both groups have same effect	0.08	0.03*
Control variables[ǂ]	Yes	
Base fixed effects	Yes	
Year effects	Yes	
Standard errors clustered at base level	Yes	
Observations	36,715	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 9a: Peer Effects by Income and Income of Peers

		Dependent variable is probability of:	
		Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:	Individual being influenced:		
Higher income	Higher income	0.8022***	0.0482
		(0.28)	(0.16)
Higher income	Lower income	0.6523**	0.1615
		(0.27)	(0.16)
p-value for test of equal effect on both types of individuals		0.11	0.30
Lower income	Higher income	0.6450**	0.1702
		(0.27)	(0.16)
Lower income	Lower income	0.8283***	0.0493
		(0.27)	(0.16)
p-value for test of equal effect on both types of individuals		0.001***	0.668
Fraction of the following group on base who carpool:	Individual being influenced:		
Higher income	Higher income	-0.738*	1.263***
		(0.39)	(0.28)
Higher income	Lower income	0.4358*	-0.08
		(0.25)	(0.19)
p-value for test of equal effect on both types of individuals		0.599	0.000***
Lower income	Higher income	0.727**	-0.29
		(0.30)	(0.23)
Lower income	Lower income	-0.111	0.676***
		(0.25)	(0.17)
p-value for test of equal effect on both types of individuals		0.54	0.0003***
Control variables‡		Yes	
Base fixed effects		Yes	
Year effects		Yes	
Standard errors clustered at base level		Yes	
Observations		37,431	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

‡ We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 9b: Peer Effects by Education and Education of Peers

		Dependent variable is probability of:	
		Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:	Individual being influenced:		
Higher education	Higher education	0.693***	-0.15***
		(0.04)	(0.03)
Higher education	Lower education	0.531***	-0.04
		(0.04)	(0.03)
p-value for test of equal effect on both types of individuals		0.07	0.96
Lower education	Higher education	0.554***	-0.03
		(0.03)	(0.02)
Lower education	Lower education	0.590***	-0.05***
		(0.03)	(0.02)
p-value for test of equal effect on both types of individuals		0.5979	0.87
Fraction of the following group on base who carpool:	Individual being influenced:		
Higher education	Higher education	-0.14	0.608
		(0.79)	(0.63)
Higher education	Lower education	0.288*	0.105
		(0.16)	(0.15)
p-value for test of equal effect on both types of individuals		0.90	0.42
Lower education	Higher education	0.450	0.095
		(0.33)	(0.24)
Lower education	Lower education	0.068	0.608***
		(0.14)	(0.12)
p-value for test of equal effect on both types of individuals		0.63	0.0822
Control variables[ǂ]		Yes	
Base fixed effects		Yes	
Year effects		Yes	
Standard errors clustered at base level		Yes	
Observations		37,431	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 9c: Peer Effects by Age and Age of Peers

		Dependent variable is probability of:	
		Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:	Individual being influenced:		
Higher age	Higher age	-10.1***	4.729***
		(2.31)	(1.46)
Higher age	Lower age	-2.27***	0.924***
		(0.53)	(0.41)
p-value for test of equal effect on both types of individuals		0.00***	0.00***
Lower age	Higher age	0.271***	-0.05***
		(0.02)	(0.01)
Lower age	Lower age	0.395***	-0.08***
		-0.02	(0.01)
p-value for test of equal effect on both types of individuals		0.00***	0.00***
Fraction of the following group on base who carpool:	Individual being influenced:		
Higher age	Higher age	3.786***	1.138
		(1.46)	(0.81)
Higher age	Lower age	-7.69***	2.450**
		(1.92)	(1.22)
p-value for test of equal effect on both types of individuals		0.61	0.31
Lower age	Higher age	0.347**	(0.04)
		(0.07)	(0.04)
Lower age	Lower age	-0.21***	0.491***
		(0.05)	(0.03)
p-value for test of equal effect on both types of individuals		0.97	0.00***
Control variables[ǂ]		Yes	
Base fixed effects		Yes	
Year effects		Yes	
Standard errors clustered at base level		Yes	
Observations		37,431	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 9d: Peer Effects by Seniority and Seniority of Peers

		Dependent variable is probability of: Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:	Individual being influenced:		
More senior	More senior	0.079	0.045
		(0.13)	-0.06
More senior	More junior	-0.24**	0.113**
		(0.11)	-0.05
p-value for test of equal effect on both types of individuals		0.00***	0.00***
More junior	More senior	2.464***	-1.13***
		(0.79)	-0.59
More junior	More junior	0.408***	-0.15***
		(0.08)	-0.05
p-value for test of equal effect on both types of individuals		0.03*	0.40
Fraction of the following group on base who carpool:	Individual being influenced:		
More senior	More senior	-0.78***	0.798***
		(0.27)	(0.17)
More senior	More junior	-0.16	0.052
		(0.19)	(0.12)
p-value for test of equal effect on both types of individuals		0.57	0.00***
More junior	More senior	0.180*	-0.01
		(0.10)	(0.09)
More junior	More junior	-0.61***	0.671***
		(0.18)	(0.15)
p-value for test of equal effect on both types of individuals		0.20	0.0910
Control variables[ǂ]		Yes	
Base fixed effects		Yes	
Year effects		Yes	
Standard errors clustered at base level		Yes	
Observations		13,164	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

ǂ We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

TABLE 9e: Peer Effects by Gender and Gender of Peers

		Dependent variable is probability of:	
		Driving Alone	*Carpooling*
Fraction of the following group on base who drive alone:	Individual being influenced:		
Female	Female	0.540***	-0.114***
		(0.04)	(0.03)
Female	Male	-0.033*	0.032*
		(0.02)	(0.02)
p-value for test of equal effect on both types of individuals		0.00***	0.00***
Male	Female	0.040	0.054
		(0.07)	(0.05)
Male	Male	0.487***	0.054
		(0.09)	(0.06)
p-value for test of equal effect on both types of individuals		0.00***	0.00***
Fraction of the following group on base who carpool:	Individual being influenced:		
Female	Female	-0.059	0.430***
		(0.07)	(0.05)
Female	Male	-0.079	0.134
		(0.16)	(0.22)
p-value for test of equal effect on both types of individuals		0.11	0.10
Male	Female	-0.005	-0.0005
		(0.04)	(0.03)
Male	Male	-0.218	0.706***
		(0.14)	(0.11)
p-value for test of equal effect on both types of individuals		0.00***	0.00***
Control variables[ǂ]		Yes	
Base fixed effects		Yes	
Year effects		Yes	
Standard errors clustered at base level		Yes	
Observations		36,715	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered at the base level are 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 of base workers who drive alone is instrumented with the fraction of base workers who are born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

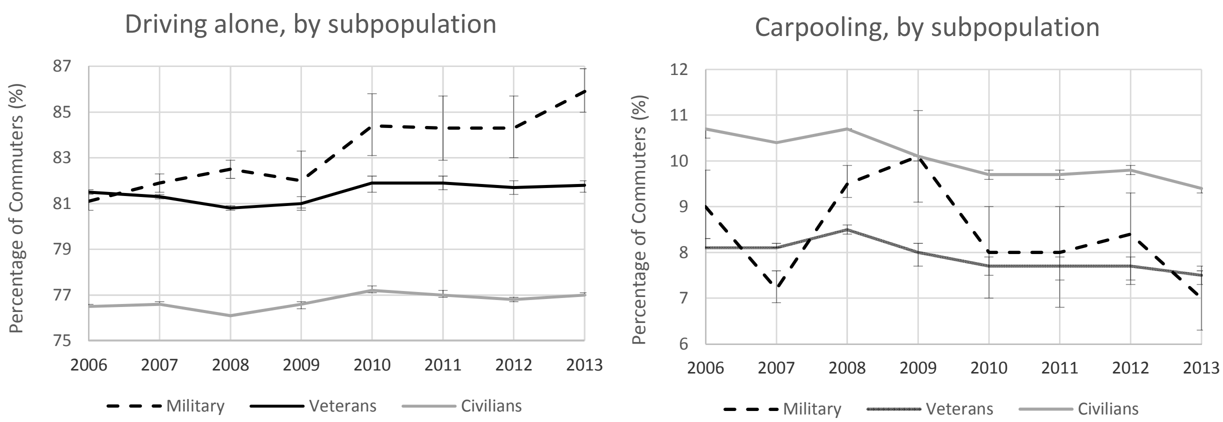
APPENDIX A: Military versus Civilian Commuters

In this Appendix, we investigate how military commuters differ from civilian commuters. To do this, we compare distributions of each control variable for three commuter groups in the U.S.: military, veterans, and civilians. The veteran group is included because they are still linked to the military (via their prior career) but are no longer influenced by the same built environment variables or workplace social influence variables.[15] We then estimate a discrete choice model using data on all U.S. commuters (and dummy variables for military members and veterans) to understand whether being in the military or a veteran has an effect on the probability of driving or driving alone when controlling for socio-economic, demographic, and built environment variables. Note that in this Appendix, we use observations of all U.S. commuters, whereas in the paper we use a military-only subgroup of commuters.

Figure A1 plots the percentage of military, veterans, and civilians who drive alone to work who carpool to work over the period 2006 to 2013. A higher percentage of military personnel drive alone to work than civilians. A lower percentage of military personnel carpool than civilians.

[15] However, it is likely that some self-selection still occurs since veterans often still live in cities with military bases (Ruggles et al., 2015).

Figure A1: Percentage of military, veterans, and civilians who drive alone to work and who carpool to work



Note: Error bars indicate 95% confidence intervals.

Data source: Ruggles et al., 2015

A.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 A1 gives summary statistics for individual-level variables for both military and civilian workers including socio-economic, immigration-related, and family-related variables.[16]

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 alone at a higher frequency and carpools at a lower frequency than civilian counterparts.

[16] 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.

Past research examining the individual-level predictors of driving alone suggests that age and vehicles per adult household member are positively related to the decision to drive alone (Belz and Lee, 2012). Table A1 demonstrates that, for these variables, military members have lower mean age than civilian commuters on the one hand and slightly more vehicles per adult in household than civilian commuters do on the other hand. Thus, military members have some characteristics that make them more likely to drive alone, and other characteristics that make them less likely to drive alone.

A.2 Built Environment Variables

Table A2 gives a similar comparison of PUMA-level built environment variables. As seen in this table, military workers tend to live in places with locations with lower worker and bus densities than civilians do. Past research suggests a negative relationship between residential density and the decision to drive, 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 residences 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) (U.S. DoD, 2015). Military personnel entering a base must pass through security gates which can act as bottlenecks for the morning commute and which might discourage non-auto modes, since the security gates are designed for cars.

Tables A3 and A4 compare the individual-level and built environment variables, respectively, for veterans and civilian workers.

TABLE A1: Two Sample t-Tests of Military and Civilian Worker Populations (2006-2013 ACS)

	Civilian Workers				Military Workers				
Sample size	n = 8,036,508				n = 37,475				Sig
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Commute									
Drive alone to work (dummy) [alternatives are carpool, bus, train, ferry, taxi, walk, cycle, work at home, other]	0.77	0.42	0.00	1.00	0.83	0.37	0.00	1.00	***
Carpool (dummy) [alternatives are drive alone, bus, train, ferry, taxi, walk, cycle, work at home, other]	0.10	0.30	0.00	1.00	0.09	0.28	0.00	1.00	***
Socio-economic / Demographic									
Age (years)	39.49	12.14	17	62	32.02	8.27	17	61	***
Education level (years)	76.70	23.23	2	116	80.57	18.32	2	116	***
Female (dummy)	0.49	0.50	0	1	0.14	0.35	0	1	***
Family									
Family income ($10,000)	8.33	7.81	-4.00	354	6.97	4.51	0.021	76	***
Hours worked per week (hours)	39.60	11.78	1	99	50.79	13.62	1	99	***
Family size (number)	2.91	1.63	1	20	2.82	1.51	1	13	
Vehicles per adult in household (number)	0.945	0.70	0	6	0.949	0.73	0	6	***
Number of children (number)	0.82	1.12	0	9	0.99	1.17	0	9	***
Immigration									
Born in Latin America (dummy)	0.002	0.05	0	1	0.004	0.06	0	1	***
Immigrated to US 0-5 years ago (dummy)	0.03	0.16	0	1	0.01	0.08	0	1	***
Immigrated to US 5-10 years ago (dummy)	0.03	0.18	0	1	0.01	0.10	0	1	***
Immigrated to US >10 years ago (dummy)	0.13	0.34	0	1	0.07	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 A2: Two Sample t-Tests for Military and Civilian Built Environments (2006-2013 ACS)

	Civilian Workers n = 8,036,508				Military Workers n = 37,475				Sig
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Worker density (workers/sq. km)	5.47	13.23	0.001	193	2.48	5.38	0.001	193	***
Bus density (bus workers/sq. km)	0.03	0.10	0	2.03	0.01	0.04	0	1.60	***
Lives in city center (dummy)	0.14	0.35	0	1	0.12	0.33	0	1	**
Lives in rural area (dummy)	0.13	0.33	0	1	0.11	0.32	0	1	***
Lives in suburban area (dummy)	0.31	0.46	0	1	0.27	0.44	0	1	***
Lives in city center, other (dummy)	0.41	0.47	0	1	0.40	0.49	0	1	
Log of state gasoline price ($)	1.08	0.16	0.73	1.47	1.07	0.17	0.73	1.47	***

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 A3: Two Sample t-Tests of Veterans and Civilian Worker Populations (2006-2013 ACS)

	Civilian Workers				Veteran Workers				
Sample size	n = 8,036,508				n = 562,310				Sig
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Commute									
Drive alone to work (dummy) [alternatives are carpool, bus, train, ferry, taxi, walk, cycle, work at home, other]	0.77	0.42	0	1	0.83	0.37	0	1	***
Carpool (dummy) [alternatives are drive alone, bus, train, ferry, taxi, walk, cycle, work at home, other]	0.10	0.30	0	1	0.09	0.28	0	1	***
Socio-economic / Demographic									
Age (years)	39.49	12.14	17	62	46.86	10.81	17	62	***
Education level (years)	76.70	23.23	2	116	77.80	18.75	2	116	***
Female (dummy)	0.49	0.50	0	1	0.10	0.30	0	1	***
Family									
Family income ($10,000)	8.33	7.81	-4	354	8.71	6.91	-3	170	***
Hours worked per week (hours)	39.60	11.78	1	99	43.39	10.99	1	99	***
Family size (number)	2.91	1.63	1	20	2.66	1.44	1	17	
Vehicles per adult in household (number)	0.95	0.70	0	6	1.03	0.67	0	6	***
Number of children (number)	0.82	1.12	0	9	0.77	1.08	0	9	***
Immigration									
Born in Latin America (dummy)	0.002	0.05	0	1	0.003	0.05	0	1	***
Immigrated to US 0-5 years ago (dummy)	0.03	0.16	0	1	0.00	0.04	0	1	***
Immigrated to US 5-10 years ago (dummy)	0.03	0.18	0	1	0.00	0.05	0	1	***
Immigrated to US >10 years ago (dummy)	0.13	0.34	0	1	0.05	0.22	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 A4: Two Sample t-Tests of Veterans and Civilian Built Environments (2006-2013 ACS)

	Civilian Workers n = 8,036,508				Veteran Workers n = 562,310				Sig
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	
Worker density (workers/sq. km)	5.47	13.23	0.001	193	2.92	6.82	0.001	193	***
Bus density (bus workers/sq. km)	0.03	0.10	0	2.03	0.02	0.05	0	2.03	***
Lives in city center (dummy)	0.14	0.35	0	1	0.11	0.31	0	1	**
Lives in rural area (dummy)	0.13	0.33	0	1	0.16	0.36	0	1	***
Lives in suburban area (dummy)	0.31	0.46	0	1	0.31	0.46	0	1	***
Lives in city center, other (dummy)	0.42	0.47	0	1	0.43	0.47	0	1	
Log of state gasoline price ($)	1.08	0.16	0.73	1.47	1.07	0.17	0.73	1.47	***

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.

A.3 General Population Models

To assess whether the military and civilians differ in their propensity for driving alone and carpooling we estimate a multinomial logit model of the commute choice decision a_{it}, where $a_{it} = 1$ indicates that individual *i* drove alone to work in year *t*, $a_{it} = 2$ indicates that individual *i* carpooled to work in year *t*, and $a_{it} = 0$ indicates that individual *i* did not drive to work in year *t*. We use as regressors control variables x_{it} which have been shown to predict commute decisions (Bento et al., 2005) as well as state fixed effects and year effects. The multinomial logit model is given by:

$$\Pr(a_{it} = j) = \frac{\exp(x_{it}'\beta_j)}{\sum_{\tilde{j}=0}^{2} \exp(x_{it}'\beta_{\tilde{j}})}, \tag{A1}$$

where $\Pr(\cdot)$ denotes probability, and β_j is a vector of parameters for commute choice decision *j* that is of the same length as x_{it}.

We estimate our multinomial commute choice model using the same military and civilian individuals used in Tables A1 and A2 and include dummy variables for being in the military and being a recent or not a recent veteran. Significant coefficients for the military dummy variables would suggest that factors beyond common predictors of travel contribute to differences in travel choices between the military/veteran individuals and the general population.

Table A5 reports the estimated marginal effects from the multinomial logit model. All military and veteran dummy variables have a significant and positive effect on the decision to drive alone. All military and veteran dummy variables have a negative effect on the decision to carpool, and all except one is significant at a 0.1% level. Being in the military increases the probability of driving alone by 1.4 to 7.5 percentage points and decreases the probability of carpooling by 1 to 4 percentage points relative to civilians. Being a veteran increases the probability of driving alone by 7.9 to 11.7 percentage points and decreases the probability of carpooling by 0.03 to 2 percentage points relative to civilians.

In Table A6, we present results of two robustness checks. In one model, we change the income control from the natural log of income to the level of income (in units of $10,000), which allows for the inclusion of observations for which the reported income level was 0. Only about 0.035% of the sample, or 3,047 observations, report an income level of 0. In the second robustness test, we only consider heads of households instead of all working household members. This helps control for inherent homogeneity between household members; such a specification has been used in previous travel research on U.S. Census data (Marion and Horner, 2007). Our results that being in the military or a veteran increases the probability of driving alone and decreases the probability of carpooling are robust across these specifications.

TABLE A5: General Population Multinomial Logit Model

	Dependent variable is probability of:	
	Driving Alone	*Carpooling*
	(1)	
Military-related		
Military member in 2006 (dummy)	0.021**	-0.022***
	(0.01)	(0.004)
Military member in 2007 (dummy)	0.032***	-0.04***
	(0.01)	(0.01)
Military member in 2008 (dummy)	0.042***	-0.01***
	(0.01)	(0.01)
Military member in 2009 (dummy)	0.036***	-0.00
	(0.01)	(0.01)
Military member in 2010 (dummy)	0.056***	-0.02***
	(0.01)	(0.01)
Military member in 2011 (dummy)	0.054***	-0.02***
	(0.01)	(0.01)
Military member in 2012 (dummy)	0.075***	-0.02***
	(0.01)	(0.01)
Military member in 2013 (dummy)	0.073***	-0.02***
	(0.01)	(0.01)
Veteran, separated > 1 year ago (dummy)	0.014***	-0.0003***
	(0.001)	(0.0001)
Veteran, separated <= 1 year ago (dummy)	0.061***	-0.020***
	(0.01)	(0.004)
Socio-economic/Demographic		
Age (yrs)	0.003***	-0.003***
	(0.0005)	(0.001)
Age-squared (yrs^2)	-0.004***	0.0002
	(0.001)	(0.0002)
Education (10s of years)	0.0003***	-0.0080***
	(0.001)	(0.0001)
Female (dummy)	0.014***	-0.007***
	(0.002)	(0.001)
Family		
Log of Family Income ($10,000)	0.034***	-0.010***
	(0.00)	(0.001)
Hours worked per week (100 hours)	0.00002***	0.00004***
	(0.00001)	(0.00001)
Family size (100s of people)	0.001	0.0070***
	(0.002)	(0.0002)

Vehicles per adult in household (number)	0.088***	-0.01***
	(0.01)	(0.001)
Number of children (100s)	0.016***	-0.002***
	(0.002)	(0.001)
Immigration		
Born in Latin America (dummy)	-0.022***	0.014***
	(0.001)	(0.001)
Immigrated to U.S. 0-5 years ago (dummy)	-0.143***	0.079***
	(0.001)	(0.001)
Immigrated to U.S. 5-10 years ago (dummy)	-0.06***	0.048***
	(0.01)	(0.001)
Immigrated to U.S. >10 years ago (dummy)	-0.01***	0.022***
	(0.01)	(0.001)
Built Environment		
Workers density (million workers/sq. km)	-0.0004***	0.0003
	(0.0001)	(0.001)
Bus density (1,000 bus workers/sq. km)	0.008	-0.01
	(0.02)	(0.02)
Lives in city center (dummy)	-0.03***	0.0003
	(0.01)	(0.001)
Lives in rural area (dummy)	-0.010***	0.010***
	(0.001)	(0.001)
Lives in suburban area (dummy)	0.009***	-0.003***
	(0.001)	(0.001)
State-level		
Log of state gasoline price ($)	-0.09**	0.045**
	(0.04)	(0.02)
State fixed effects	Yes	
Year fixed effects	Yes	
Observations	8,595,771	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors in parentheses. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

TABLE A6: Robustness Checks for General Population Models

	Dependent variable is probability of:			
	Driving Alone	*Carpooling*	*Driving Alone*	*Carpooling*
	Income in level instead of log		Heads of households only	
	(2)		(3)	
Military member in 2006 (dummy)	0.020*	-0.023*	0.034*	-0.014*
	(0.01)	(0.004)	(0.01)	(0.004)
Military member in 2007 (dummy)	0.030***	-0.04***	0.054***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Military member in 2008 (dummy)	0.042***	-0.01***	0.060***	-0.01***
	(0.01)	(0.01)	(0.01)	(0.01)
Military member in 2009 (dummy)	0.036***	-0.00008	0.062***	-0.012***
	(0.01)	(0.01)	(0.01)	(0.004)
Military member in 2010 (dummy)	0.057***	-0.02***	0.074***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Military member in 2011 (dummy)	0.055***	-0.02***	0.065***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Military member in 2012 (dummy)	0.074***	-0.02***	0.085***	-0.02***
	(0.01)	(0.01)	(0.02)	(0.01)
Military member in 2013 (dummy)	0.073***	-0.02***	0.085***	-0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Veteran, separated <= 1 year ago (dummy)	0.015***	-0.005***	0.014***	-0.005***
	(0.003)	(0.001)	(0.001)	(0.001)
Veteran, separated > 1 year ago (dummy)	0.062***	-0.02***	0.071***	-0.024***
	(0.01)	(0.001)	(0.01)	(0.001)
Control variables[ǂ]	Yes		Yes	
State fixed effects	Yes		Yes	
Year effects	Yes		Yes	
Observations	8,598,818		4,545,945	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors in parentheses. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.

[ǂ] We use the following control variables:

Individual-level: age, age-squared, education level, female, income, hours worked per week, family size, vehicles per adult in household, number of children, born in Latin America, immigrated to U.S. 0-5 years ago, immigrated to U.S. 5-10 years ago, immigrated to U.S. more than 10 years ago

Built environment/Other: worker density (workers/sq-km), bus density (bus workers/sq-km), lives in city center, lives in rural environment, lives in a suburban environment, state gasoline price

APPENDIX B: Robustness checks

Table B1. Alternative specifications for multinomial logit military peer effects model

	Dependent variable is probability of:							
	Driving Alone	*Carpooling*	*Driving Alone*	*Carpooling*	*Driving Alone*	*Carpooling*	*Driving Alone*	*Carpooling*
	No weighting		No instruments		All military		All military, no instruments	
	(2)		(3)		(4)		(5)	
Endogenous Peer Effect Variables								
Fraction of military personnel on base who drive alone	0.752***	-0.13**	0.578***	-0.06***	0.830***	-0.15	0.918***	-0.08**
	(0.20)	(0.06)	(0.03)	(0.02)	(0.22)	(0.09)	(0.06)	(0.03)
Fraction of military personnel on base who carpool	22.91	-3.81	-0.08*	0.563***	39.73*	-3.61	-0.00	0.840***
	(15.09)	(5.22)	(0.05)	(0.04)	(23.40)	(10.20)	(0.12)	(0.06)
Socio-economic/Demographic								
Age (yrs)	0.047***	-0.020***	0.023***	-0.017***	0.051***	-0.020***	0.051***	-0.020***
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Age-squared (yrs^2)	-0.00060***	0.00022***	-0.0003***	0.000***	-0.0006***	0.00022***	-0.0006***	0.00021***
	(0.00004)	(0.00002)	(0.00003)	(0.00)	(0.00004)	(0.00002)	(0.00004)	(0.0002)
Education (10s of years)	0.00005**	-0.0008***	0.00003*	-0.0003**	0.00034	-0.0005***	0.0003	-0.0005***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0002)
Female (dummy)	-0.01*	0.045***	-0.02***	0.034***	-0.008	0.036***	-0.008	0.036***
	(0.01)	(0.005)	(0.01)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)
Family								
Log of Family Income ($10,000)	0.012**	0.002	0.007**	-0.006**	0.017**	0.001	0.021***	0.002
	(0.01)	(0.003)	(0.004)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)
Hours worked per week (100 hours)	-0.00	-0.00001	-0.00008	0.00003	-0.00003	-0.00004	-0.00002	-0.00004
	(0.01)	(0.0001)	(0.0001)	(0.0001)	(0.00)	(0.0002)	(0.00)	(0.0002)
Family size (100s of people)	-0.03***	0.0007	-0.017***	0.005*	-0.03***	0.001	-0.03***	0.0004
	(0.01)	(0.004)	(0.003)	(0.003)	-0.005	(0.005)	(0.01)	(0.005)
Vehicles per adult in household (number)	0.030***	0.004	0.012***	0.003	0.026***	0.007*	0.024***	0.007*
	(0.01)	(0.004)	(0.004)	(0.003)	(0.01)	(0.003)	(0.01)	(0.003)
Number of children (100s)	0.036***	0.001	0.017***	-0.003	0.029***	-0.0005	0.032***	0.0001
	(0.01)	(0.004)	(0.004)	(0.003)	(0.01)	(0.0003)	(0.01)	(0.003)
Immigration								
Born in Latin America (dummy)	0.027	-0.00	0.009	0.019*	0.006	0.015	0.007	0.015
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Immigrated to U.S. 0-5 years ago (dummy)	-0.02	0.013	-0.00	-0.01	-0.02	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Immigrated to U.S. 5-10 years ago (dummy)	-0.02	0.012	-0.00	-0.00	0.00056	-0.007	0.001	-0.00

	(1)		(2)		(3)		(4)	
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Immigrated to U.S. >10 years ago (dummy)	0.023***	0.008	0.012	0.001	0.018	0.005	0.017	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)
Built Environment								
Workers density (million workers/sq. km)	0.002	-0.003**	-0.0008	-0.0008	-0.0001	-0.002	-0.003	-0.004
	(0.003)	(0.002)	(0.0008)	(0.0007)	(0.004)	(0.002)	(0.004)	(0.003)
Bus density (1,000 bus workers/sq. km)	0.089	0.055	0.013	0.027	0.815**	-0.05	0.180	-0.05
	(0.26)	(0.16)	(0.09)	(0.08)	(0.32)	(0.14)	(0.19)	(0.14)
Lives in city center (dummy)	-0.01	0.022**	0.000	0.006	-0.04	0.027	0.000	0.021*
	(0.03)	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)	(0.02)	(0.01)
Lives in rural area (dummy)	-0.05	0.012	0.001	-0.00	-0.11	0.014	0.005	-0.00
	(0.07)	(0.02)	(0.02)	(0.01)	(0.09)	(0.03)	(0.03)	(0.01)
Lives in suburban area (dummy)	0.043**	0.005	0.005	0.002	0.042***	0.005	0.029**	0.006
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)
State-level								
Log of state gasoline price ($)	0.066	-0.08	-0.13	0.015	0.048	0.052	-0.16	0.078
	(0.19)	(0.09)	(0.13)	(0.06)	(0.20)	(0.08)	(0.18)	(0.08)
Residuals								
Residual from Fraction who drive alone 1st stage	0.089	0.050			-39.7*	4.454		
	(0.19)	(0.06)			(23.40)	(10.20)		
Residual from Fraction who carpool 1st stage	-22.7	4.381			0.010	0.057		
	(15.12)	(5.22)			(0.19)	(0.09)		
Base fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Standard errors clustered at base level	Yes		Yes		Yes		Yes	
Observations	37,475		37,475		53,976		53,976	

Notes: Marginal effects at the mean values of the covariates are reported. Standard errors clustered by base are in parentheses. For specifications (1) and (3), the fraction of base workers who drive alone is instrumented with the fraction of base workers born in Latin America, and the fraction of base workers who carpool is instrumented with the fraction of base workers who immigrated to the United States 5-10 years ago. Significance codes: * 5% level, ** 1% level, and *** 0.1% level.