Does Employment Growth Increase Travel Time to Work?: An Empirical Analysis using Military Troop Movements[1]

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ABSTRACT

Employment growth is a common public policy goal, but it can lead to a number of unwanted environmental, social, and economic costs – particularly in high growth communities – due to its impact on peak-hour traffic. This paper examines the short-run impacts of rapid employment growth on travel time to work. We exploit exogenous variation in employment levels resulting from movements of military troops during the 2005 Base Realignment and Closure (BRAC) in order to identify the effect of employment growth on travel time using difference-in-difference-in-differences and instrumental variable methods. Our results show that for each additional 10 workers added per square kilometer, travel time increases by 0.171 to 0.244 minutes per one-way commute trip per commuter in the short run, which equates to \$0.07 to \$0.20 in travel time cost per commuter per day. Our estimates imply that the annualized short-run congestion costs of the 2005 BRAC were \$79 to \$761 million per year (in constant 2005 dollars) for military commuters and \$3.15 to \$6.3 billion per year (in constant 2005 dollars) for civilian commuters in BRAC-affected areas.

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1. Introduction

Studies have shown that traffic congestion is the number one concern of individuals in rapidly growing areas in the U.S., often ranked higher than crime, school over-crowding, and housing shortages (Cervero, 1989; NJ, 2005; GAO, 2009). Traffic congestion and long travel times are undesirable because they discourage future economic growth (Hymel, 2009; Sweet, 2011), increase vehicular emissions, increase fuel expenses, increase operating costs for both private and freight vehicles, decrease economies of agglomeration, heighten the psychological burden of travel, create a need for more emergency services, decrease the reliability of travel, and impose an opportunity cost on time (Downs, 1992; Downs, 2004; Brownstone and Small, 2005; Beaudoin, Farzin and Lin Lawell, 2015; Beaudoin, Farzin and Lin Lawell, 2016; Beaudoin and Lin Lawell, 2016b).

Travel time is a function of both the speed of travel (which is affected by congestion) and the distance of travel. A number of short- and long-run factors influence these two variables. In the very short run – by which we mean hours to months – inclement weather, traffic accidents, special events, and road construction create a temporary lack of transportation supply for a given demand and thus reduce the speed of travel.

In the longer run – by which we mean years to decades – city-level factors change the number of travelers using a transportation network or the travel distances between locations (FHWA, 2012; Downs, 2004). Examples of such long-run factors include the absolute employment level (larger metropolitan areas tend to have higher congestion); infrastructure expansion or contraction; vehicle ownership; travel preferences (e.g., younger travelers increasingly prefer active modes of transport); geo-demographics; number of two-worker households; the accessibility of the transportation network; and relative distances between jobs and housing.

A final factor that influences traffic congestion is the rate of growth in travelers using the transportation network. Communities plan for growth by adding infrastructure capacity or implementing travel demand management measures. However, when the rate of growth is higher than anticipated (i.e. an employment shock) or the community lacks the ability to respond to the growth, traffic congestion may increase.[2]

In this paper, we use one measure of growth – employment growth – to estimate how growth shocks impact travel time to work.[3] Employment growth is a common public policy goal, but it can lead to a number of unwanted environmental, social, and economic costs – particularly in high growth communities – due to its impact on peak-hour traffic. A better understanding of the relationship between travel times and employment growth would help policy-makers develop more informed growth strategies.

Our focus in this paper is on the short-run, congestion-related impacts of employment growth. In the long run, employment growth tends to increase the wealth of a community and push out the boundaries of the urban area, thereby increasing the distance of travel.[4] Although the effects of employment growth on traffic congestion may be attenuated in the long run as people may respond by moving or changing jobs, and as city planners may respond by changing transportation infrastructure, an examination of the short-run effects is important because the

[2] Traffic theory suggests congestion increases when vehicle volumes reach a critical density, determined by the geometry, speed law, and condition of the road.

[3] We use travel time instead of a congestion index as the main outcome variable because it enables us to use person-level data. Additionally, despite being a simple concept in practice, traffic congestion is difficult to measure because of its heterogeneous nature across space and time (Downs, 2004).

[4] It should be noted that any short- or long-run factor that affects travel times will be dampened by the "triple convergence" in which commuters re-adjust to new travel conditions by switching routes, modes, and departure times (Downs, 1992; Choo and Mokhtarian, 2008).

short-run effects of employment growth on travel time and travel time costs associated with these effects, though perhaps only incurred over a short period of time, may be high.[5]

In the past three decades, employment growth rates averaged 1.4% per year in the U.S.,[6] and some high growth communities like the city of Las Vegas in the 1990s or Atlanta in the 2000s reached employment growth rates of over 10% per year (Ruggles et al., 2015). Over roughly the same period, the congestion-related delay has increased from 2 to 5 minutes per one-way commute in the U.S. (Schrank et al., 2011).[7]

There are two sources of endogeneity that must be overcome when estimating the effect of employment growth shocks on travel time. First, a simultaneity problem arises if travel time has an influence on employment growth. This could occur if an increase in average travel times reduces the attractiveness of a community to potential new firms. This, in turn, reduces the number of future commuters using the transportation network (Hymel, 2009; Sweet, 2011) and incentivizes new residents and businesses to locate on the outskirts of the city or in another city altogether (Downs, 1992). A second endogeneity problem stems from omitted variables, such as transportation infrastructure, that are related to both employment growth and travel time. Any factor in a community that may have changed in anticipation of an upcoming employment boom could fall in this category.

To address these potential endogeneity issues, this paper exploits exogenous variation in employment levels resulting from movements of military troops during the 2005 Base Realignment and Closure (BRAC) process. The BRAC process provides a convenient quasi-

[5] Morever, the costs of any long-run adjustments, which may involve building infrastructure, changing jobs, and/or moving, are also potentially very high, even if they reduce congestion costs.
[6] This number reflects the percentage increase in employed workers per square kilometer in 221 metropolitan areas between 1980 and 2012. The 221 metropolitan areas are those identified by the *pwmetro* variable in Ruggles et al. (2015).
[7] These estimates apply to two-way commute (e.g. home to work to home). They are calculated using the annual delay per commuter in 1982 and 2010 according to Schrank et al. (2011) of 15 hours and 38 hours, respectively. The average number of weeks worked was 44.2 weeks in 1980 and 46.8 weeks in 2012 (Ruggles et al., 2015).

experimental framework to measure the short-run, congestion-related effects of employment growth on travel times because it occurred largely outside of the normal transportation planning process. As we argue in the paper, these exogenous troop movements address the simultaneity and omitted variable endogeneity problems that arise when estimating the effect of employment growth shocks on travel time.

We conduct two separate analyses to measure the short-run, congestion-related effects of employment growth on travel time to work. The first uses difference-in-difference-in-differences (DDD) methods in which travel times for military individuals in communities affected by the 2005 BRAC are compared to travel times for two control groups both before and after the 2005 BRAC. In the second, and preferred, analysis, we use an instrumental variable (IV) model in which we instrument for regional employment density with the change in military troops in the 2005 BRAC. The IV method enables measurement of a causal relationship between employment density and travel time.

As we use annual data and as our data set extends a few years after the 2005 BRAC, the relevant time horizon for the "short run" that we use in this paper is on the order of a year to a few years. Even in the short run, it is possible that some people may respond to employment growth by moving; or by adjusting their work schedules to depart from home to work at a different time, or to arrive at work at a different time. Our estimates therefore measure the short-run effect of employment growth after individuals have had a chance to respond by moving or adjusting their work schedules.

Our results are quite robust across models. We find that on average in the U.S. each additional 10 workers[8] added to the transportation network per square kilometer adds 0.171 to

[8] We define a "worker" as one who works for someone else for wages, salary, piece rate, commission, tips, or payments "in kind" (for example, food or lodging received as payment for work performed); works in his or her own

0.244 minutes per one-way commute trip per commuter in the short run which equates to \$0.07 to \$0.20 in travel time cost per commuter per day. Our estimates imply that the annualized short-run congestion costs of the 2005 BRAC were \$79 to \$761 million per year (in constant 2005 dollars) for military commuters and \$3.15 to \$6.3 billion per year (in constant 2005 dollars) for civilian commuters in BRAC-affected areas.

It is possible that the annual congestion costs of the 2005 BRAC may decrease over time in the long run, as more people may respond by moving or changing jobs, and as city planners may respond by changing transportation infrastructure. As our focus is on the short-run effects of employment growth, and as the BRAC occurred just recently, we are unable to estimate long-run effects. However, the short-run costs congestion costs of the 2005 BRAC are still quite high, even if they are only incurred in the first few years.

The question of how employment growth impacts region-wide travel times has tremendous relevance to city planning. Communities often prioritize job creation and give the associated traffic-induced externality less attention. This paper therefore should be useful to policy-makers who seek effective growth strategies. A better understanding of the relationship between employment growth and travel times would help planners develop effective anti-congestion measures by properly predicting expected changes in travel times due to growth.

Additionally, this paper contributes to our understanding of how military troop movements affect communities around military bases. With over 1.2 million members of the U.S. military, fluctuations in troop levels at military bases have a major impact on surrounding communities (Hampton Roads, 2007; NAS 2011), and to our knowledge no previous academic

business, professional practice, or farm; performs any work in a family business or farm, paid or not; performs any part-time work including babysitting, paper routes, etc.; and/or is active duty in the Armed Forces.

study has looked at how the movements of troops – either from base closures or from routine deployment cycles – affect a region's transportation network.

The balance of our paper proceeds as follows. We review the related literature in Section 2. In Section 3, we make the case for the exogeneity of the 2005 BRAC. Section 4 describes our data. We conduct Granger causality tests to provide further evidence for the exogeneity of the 2005 BRAC in Section 5. Section 6 presents our difference-in-difference-in-differences (DDD) analysis. Section 7 presents our instrumental variable (IV) analysis. In Section 8, we present a back-of-the-envelope estimate of the short-run travel time costs from the 2005 BRAC. Section 9 concludes.

2. Related Literature

Many congestion researchers have suggested that higher growth is associated with worsening traffic but have not empirically estimated the relationship or dealt with the endogeneity problems (Freilich and White, 1991; Downs, 2004). While few studies have empirically estimated the effects of employment growth on travel time to work, there is a small but growing literature on the effects of public transit availability on travel time to work.

Anderson (2014) uses a sudden strike of public transit workers in Los Angeles in 2003 to estimate the delay in highway travel if no public transit existed (i.e. the value of public transit in terms of avoided congestion). He finds that the average delay induced by the system shock is 0.19 additional minutes per mile of road travel during the peak travel period. As the average auto one-way commute distance in Los Angeles was 15.7 miles according to the 2001 National Household Travel Survey (NHTS), Anderson (2014) finds that the strike added on average 2.98 minutes per one-way commute.

Nelson et al. (2007) analyze the traffic delay reduction associated with the Washington D.C metro system and estimate the metro system creates a congestion relief of 184,000 person-hours per day or 2.0 person-minutes per peak transit passenger-mile.

Beaudoin and Lin Lawell (2016b) estimate the effect of public transit investment on traffic congestion by applying an instrumental variables approach that accounts for the potential endogeneity of public transit investment to a panel dataset of 96 urban areas across the U.S. for the years 1991-2011. Their results show that increases in public transit supply lead to a small overall reduction in auto traffic congestion (on average, a 10% increase in overall transit capacity leads to a 0.8% reduction in congestion). However, the magnitude of this effect is subject to heterogeneity across urban areas: the elasticity of auto travel with respect to transit capacity varies from -0.014 for smaller, less densely populated regions with less-developed public transit networks, to -0.296 in the largest, most densely populated regions with extensive public transit networks.

Other related research examines the shock of new public transit systems on air quality of cities. Chen and Whalley (2012) look at the opening of the Taipei Metro and find a 5 to 15 percent reduction in carbon monoxide level but no effect on ground-level ozone or on more general travel patterns throughout this city, despite mode shifts to metro.

Beaudoin and Lin Lawell (2016a) empirically analyze the effects of the level of transit supply on observed ambient pollution levels for 96 urban areas across the U.S. In particular, they analyze the effects of the level of transit supply on the following criteria pollutants: carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter, and sulfur dioxide. They find that – at the margin, and given existing urban travel regulations in place – there is no evidence that an increase in transit supply improves air quality.

3. Exogeneity of the 2005 BRAC

In this section we make the case that, conditional on the control variables – which include train density, bus density, whether the area is urban, whether the area is rural, lagged average commute travel time in the area, state fixed effects, and year effects – the troop movements in the 2005 BRAC were exogenous to employment growth. The exogeneity of the BRAC enables us to address potential endogeneity problems in measuring the impact of employment growth on travel time.

As discussed above, two sources of endogeneity are omitted variables and simultaneity. The 2005 BRAC would suffer from an omitted variable problem if there were omitted factors related to both the movement of troops and to changes in travel time. We identify two potential omitted variable problems: 1) the BRAC decisions could be based, at least to some degree, on characteristics of bases that are correlated with travel time, and 2) BRAC-affected communities may have taken pre-emptive or concurrent action to upgrade or expand their transportation infrastructure before or during the movement of troops. The 2005 BRAC would suffer from a simultaneity problem if travel time had an influence on the employment growth resulting from the BRAC. Below, we discuss the omitted variable problems and then the simultaneity problem.

For our DDD estimates of the treatment on the treated, we do not need the 2005 BRAC to be as good as randomly assigned. In other words, for our estimates of the effects of the 2005 BRAC on travel time, random treatment is not required.

To contextualize the discussion, we first provide a brief history of the BRAC process. In the 2005 BRAC, the Department of Defense (DoD) closed 29 bases and relocated 123,000 troops to 57 other bases in a process known as Base Realignment and Closure (BRAC). These 123,000 troops relocated over a relatively short period (between 2006 and 2011). Since the end of the Cold War, there have been five rounds of base closures (1989, 1991, 1993, 1995, and 2005) with the primary goal of reducing the DoD physical infrastructure budget and improving the military's strategic agility. Past rounds of BRAC have closed between 17 and 33 bases and the next round is tentatively scheduled for 2017.

3.1 Omitted Variable Problems

One potential omitted variable problem would arise if the BRAC decisions were based, at least to some degree, on characteristics of bases that are correlated with travel time. As in past rounds of BRAC, the decision for which bases to include/exclude in the round of closures in the 2005 BRAC was a mix of political, budgetary, and strategic interests (Beaulier et al., 2011). The first pertinent step in the BRAC process was in May 2005, when the Secretary of Defense gave the list of base recommendations to the BRAC Commission – a group of nine high ranking political and military figures appointed by the President to oversee the BRAC process. Of these recommendations, 86% were eventually approved by the Commission and authorized by the President (Beaulier et al., 2011).

The DoD used a set of eight criteria to evaluate potential bases (DoD, 2005a). Four criteria relate to how a closing/realignment will add to the ability of the military to accomplish its mission; one relates to the costs and savings to the military; another to the environmental impact of a closure or realignment; and another to the economic impact on existing and "receiving" communities (communities that receive troops). The final criterion – impact on community infrastructure – is germane to this study. This criterion considers "the ability of the infrastructure of both the existing and potential receiving communities to support forces, missions, and personnel" (p. 333, DoD, 2005a). Specifically, the infrastructure considerations include 10 sub-categories: demographics, child care, cost of living, education, employment, housing, medical providers, safety/crime, transportation, and utilities. For transportation, the two grading criteria were: (1) distance to the nearest major airport, and (2) availability of public transportation.

Although the transportation system of receiving bases was one of the 10 sub-categories of one of the eight criteria that affected decision to place troops at a base, transportation infrastructure was just one of several factors considered in the movement of troops and was not the sole driver in the selection of one receiving base versus another. Furthermore, publically available documents reveal that the grading of public transportation was done using a simple yes or no answer (e.g., "Is Fort Meade served by regularly scheduled public transportation, yes or no?") (DoD, 2005b). Of the bases that were eventually chosen to gain troops in the 2005 BRAC, 47% have "No" as the response to this public transportation grading criteria (DoD, 2005b). Such a large fraction of "No's" suggests that the availability of public transportation was not a central driver in the BRAC decision.

To test whether BRAC decisions were based on characteristics of bases that are correlated with travel time, we conduct Granger causality tests to examine whether characteristics of regions with military bases, including train density, an indicator of a region's transportation system, Granger-caused the change in the number of military individuals in the 2005 BRAC. As explained in Section 5, we find strong evidence that train density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC. Thus, BRAC decisions do not appear to be significantly based on characteristics of bases that are correlated with travel time.

Moreover, even if BRAC communities that received new troops were, on the whole, more able to absorb new commuters, then the magnitude of the effect measured here – the impact of growth on travel time to work – would be biased downwards towards zero, leading us to underestimate the impact of employment growth on travel time to work. In this case, our estimates would be a lower bound on the effect of employment growth on travel time to work. Moreover, as mentioned above, for our DDD estimates of the treatment on the treated, we do not need the 2005 BRAC to be as good as randomly assigned. In other words, for our estimates of the effects of the 2005 BRAC on travel time, random treatment is not required.

A second omitted variable problem could arise if communities receiving new troops took action to improve transportation infrastructure before the movement of troops began. We think this effect is small because of the condensed timing of events in the 2005 BRAC. Re-locations of troops in the 2005 BRAC were to begin in January 2006 and finish by September 2011. As shown in the timeline of the BRAC process in Table 1, the Department of Defense did not submit a list of bases they recommended for closing until the spring of 2005. Even if a base was on a list, however, the base was not guaranteed to be closed or realigned under the President's approval in late 2005. Media reports from the summer of 2005 indicate real estate investors were hesitant to make real estate transactions until the final recommendations were made in September 2005 (Hedgepeth, 2005). This suggests that other transportation infrastructure projects would also not have begun until the final approval of the BRAC bases.

Furthermore, expanding transportation infrastructure requires a long lead time because of the numerous steps involved. Detailed traffic studies are conducted followed by a planning and design phase and then by public discussion, permitting, and construction. Thus, it is unlikely that the increased demand for travel from the 2005 BRAC would have been met with the expansion of infrastructure capacity in the short run. We interviewed a senior transportation planner in the Fort Bragg, NC region who stated that transportation planning pertaining to BRAC growth was conducted after 2005, that transportation capacity expansion projects in his region took at least seven years to complete, and that the first projects related to BRAC growth were not completed until 2012 (Strickland, 2015).

The Washington DC area – a region with numerous BRAC-affected bases – provides an example of how BRAC communities did not preemptively build transportation infrastructure before 2005. After the final list of base realignments was announced in the fall of 2005, the Maryland Highway Administration revealed plans to expand Route 175 to help facilitate the additional troops at Fort Meade, Maryland. By the September 2011 deadline for completion of the BRAC process, the additional lanes of highway still had not been added (Washington Post, 2011). In response to public criticism towards the BRAC-related traffic congestion, the head of the Washington, DC Metropolitan Planning Organization exclaimed: "We just don't have the resources to add capacity when they [U.S. Congress] just drop these things [BRAC] out of the sky," (Halsey, 2011). Funding for building new transportation infrastructure to address BRAC-related traffic congestion was allocated to the Washington, DC area as late as 2014 (Van Hollen, 2014).

A National Academies of Science (2011) report on the 2005 BRAC suggests that lack of transportation capacity was a central challenge in the 2005 BRAC: "The problems for state and local jurisdictions in BRAC cases are attributable to the rapid pace of traffic growth on heavily used facilities….The normal length of time for development of highway and transit projects – from required planning and environmental processes all the way through construction – is, at best, nine years and usually 15 to 20 years" (p. 7, NAS, 2011). The NAS report concludes that the BRAC timeline gave insufficient opportunity for receiving communities to properly conduct transportation planning. An earlier Government Accountability Office report from 2009 comes to similar conclusions: "Growth resulting from the BRAC decisions will have a significant impact on transportation systems in some communities… BRAC growth will result in increased traffic in communities ranging from very large metropolitan areas to small communities, creating or worsening congested roads at specific locations." (GAO, 2009, p. 2).

In sum, communities receiving new troops had little time to take action before the movement of troops began in 2005. Although communities eventually began transportation improvement projects, the long lag time between funding and completion meant these projects were often not completed by 2011.

To test whether communities receiving new troops took action to improve transportation infrastructure before the movement of troops began, we conduct Granger causality tests to examine whether train density, an indicator of a region's transportation system, Granger-caused the change in the number of military individuals in the 2005 BRAC. As explained in Section 5, we find strong evidence that train density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC. Thus, neither omitted variable problem is likely to be an issue.

3.2 Simultaneity Problems

The 2005 BRAC would suffer from a simultaneity problem if travel time had an influence on the employment growth resulting from the BRAC. One way this may arise is if travel time had an influence on which bases were affected by BRAC. We feel the 2005 BRAC is free from potential simultaneity problems because of the nature and timing of the BRAC process.

The 2005 BRAC occurred as a result of an exogenous, top-down governmental requirement, not as part of a normal employer location decision. There is no documentation that we can find suggesting the government adjusted the number of troops it sent to an area because of increasing levels of congestion.

To test whether travel time had an influence on which bases were affected by BRAC, we conduct Granger causality tests to examine whether commute travel time Granger-caused the change in the number of military individuals in the 2005 BRAC. As explained in Section 5, we find strong evidence that commute travel time did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC.

A simultaneity problem could also arise between the 2005 BRAC and travel time if the increased congestion from the 2005 BRAC caused civilian firms to relocate their employees elsewhere. Another possibility is that additional troops in a community attract new employment – particularly retail and service jobs – and thus amplify the traffic impacts.

We address these simultaneity problems resulting from employment feedback in several ways. First, this employment feedback is a long-run phenomenon and therefore less of a concern for our short-run analysis. In his study of the effect of traffic-related feedback on employment growth in Los Angeles, Hymel (2009) finds that it takes at least 10 years for increased traffic congestion to dampen employment growth.

Second, in our IV regressions we instrument for employment density using change in military troops under the 2005 BRAC and therefore isolate the exogenous component of the employment growth from any endogenous employment feedback, whether positive or negative. This enables us to control for any induced changes in civilian employment.

Third, if the 2005 BRAC decreased civilian employment, then when using the 2005 BRAC to measure employment growth, our estimates of the impact of growth on travel time to work would be biased downwards towards zero, leading us to underestimate the impact of employment growth on travel time to work. In this case, our estimates would be a lower bound on the effect of employment growth on travel time to work.

Fourth, we estimate a version of our IV regression in which we restrict the sample to only individuals who have lived in the same house since before 2005, which enables us to examine the effects of the employment growth resulting from the 2005 BRAC on the civilian individuals who were already in the area and did not move. Since a possible response to an increase in employment growth is to move, restricting our sample to those who did not move enables us to estimate a very short-run effect of employment growth, before individuals have a chance to respond by moving. In contrast, our base case IV regressions, which do not restrict the sample to those who did not move, estimate the short-run effect of employment growth after individuals have had a chance to respond by moving. As explained in Section 7, we find that the very short-run effect of employment growth on commute travel time can be quite high, and is higher than the short-run effect of employment growth after individuals have had a chance to respond by moving.

4. Data

Using military troop movements as exogenous employment shocks has advantages over using movements of other populations. The Department of Defense maintains public records of troop levels at its bases. This allows tracking the exact number of employees who commute to each base in each year. Also, the U.S. military is relatively homogenous between bases in its demographic composition meaning that when troop levels change on a base, we expect the effect to be uniform across bases. On the other hand, military bases exist in a geographically diverse set of cities and towns allowing the examination of the effect of employment growth shocks on different parts of the country.

There are also disadvantages to using a population of military for this analysis. First, a number of important differences exist between commuting to a military base and commuting to an average workplace. According to 2000-2010 census data, the average departure time for work was 7:45am for military workers and 8:32am for civilians (Ruggles et al., 2015). Therefore, military members commute at slightly off-peak times which would likely lessen a change in travel time due to BRAC. Military commuters also have fewer alternatives to driving than civilians because of the lack of public transit, the lack of an option to telecommute, and the often low density built environment on base.[9] Military members also generally have a greater preference for driving to work than their civilian counterparts – 92% of military commute by auto while 87% of civilians commute by auto (Morrison and Lin Lawell, 2016; Ruggles et al., 2015). A higher drive-to-work rate could have an amplification effect on traffic congestion in the face of employment growth. Also, military commuters must pass through security gates on their way to work. The impact of these gates is not quantified here, although the gates likely amplify the travel delay in congested regions (FHWA, 2004). To partially address the drawbacks of using a military population, we analyze the effects of employment growth on travel time to work for both the military population as well as the civilian population, and we apply our instrumental variables regressions to the entire US.

[9] Military bases have a range of different land uses and transit availability.

For this study, we identify 57 bases that received troops as part of the 2005 BRAC. A map of these bases is presented in Figure 1. Additionally, we identify 43 bases that lost troops and 36 bases that were not affected in the 2005 BRAC.

We use person-level, repeated cross-section data from the 2000 decennial census and the 2005-2010 American Community Surveys (ACS), available through the University of Minnesota's IPUMS website (Ruggles et al., 2015). The years 2001-2004 were the first years of the ACS and are omitted here because they do not include a complete set of control variables. The U.S. Census Bureau uses a multistage sampling design to ensure a representative sample each year which includes stratification, clustering, and weighting of individuals.[10] An individual's residence and workplace in census data are only known within regions called PUMAs containing approximately 100,000 people. However, for individuals in the military, a combination of their service affiliation (e.g. Air Force, Army, etc.) and their workplace region allows assignment of that individual to a specific military base. For example, individual XX is known to work at Fort Meade, Maryland which is located in PUMA YY. For the military population, we only consider military individuals who are commuting from private houses or apartment buildings off-base and we omit those who live on-base in barracks or on ships.[11] Our travel time data come from the question in the American Community Surveys that asks: "How many minutes did it take the respondent to get from home to work last week?" (Ruggles et al., 2015).

[10] As recommended by Ruggles et al. (2015), to help correct for the homogeneity of individuals in the same household and geographic region, our models use a Taylor Series Linearization (TSL) procedure in which an individual's household is the primary sampling unit and an individual's residential geographic area (PUMA) is the stratum.

[11] Military troops that live off-base in the surrounding community comprise approximately 75% of the military community.

Data on the number of troops moved as part of the 2005 BRAC come from the Department of Defense (2005; 2006; 2007; 2008; 2009; 2010) and are reported as the number of troops at a base at the beginning of a fiscal year. The number of troops received during the BRAC in each PUMA ranges from 12 to 11,763 troops over the five-year period.

Table 2 shows summary statistics of the military population in BRAC-affected PUMAs and the U.S. general population for all variables used in the analysis. The sample sizes used in models in this paper are extremely large, ranging from 20,162 to 9.60 million observations. Summary statistics for all subgroups considered in the DDD and IV analyses are available in Tables A1 and A2, respectively, in Appendix A.

Table 3 presents the variation in one-way travel time to work across years for a given PUMA ("within") and the variation in travel time to work across PUMAs for a given year ("between"). We calculated the within and between variation for all PUMAs in the U.S. as well as for all BRAC-affected PUMAs for the years 2000-2010. The variation in travel time to work across PUMAs for a given year ("between") is larger than the variation in one-way travel time to work across years for a given PUMA ("within").

5. Granger Causality Tests

To further examine the exogeneity of the 2005 BRAC, we conduct a Granger causality test (Granger, 1969; Hamilton, 1994) to test whether commute travel time Granger-caused the change in the number of military individuals in the 2005 BRAC. This test uses a two-variable vector autoregressive (VAR) model followed by a Wald test to examine the potential endogeneity between travel time to work and the change in the number of military individuals in the 2005 BRAC.

We test for Granger causality in each of the 136 PUMAs that have military bases.[12] For each of the 136 PUMAs, we first estimate the following VAR model:

$$BRAC_t = \alpha_0 + \alpha_1 BRAC_{t-1} + \alpha_2 TT_{t-1} + \varepsilon_t \quad (1)$$

$$TT_t = \beta_0 + \beta_1 TT_{t-1} + \beta_2 BRAC_{t-1} + \mu_t, \quad (2)$$

where $BRAC_t$ is the change in the number of military individuals in the 2005 BRAC and TT_t is the log average commute travel time. We then test for Granger causality in each of the 136 PUMAs.

Applying the Bonferroni correction to adjust for multiple hypothesis testing (Bland and Altman, 1995; Napierala, 2012), we find that average commute travel time did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC at a 5% level in all but 4% of the 136 PUMAs with military bases. We therefore find strong evidence that average commute travel time did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC.

We also conduct a second Granger causality test to test whether worker density[13] Granger-caused the change in the number of military individuals in the 2005 BRAC. We test for Granger causality in each of the 136 PUMAs that have military bases. For each of the 136 PUMAs, we first estimate the following VAR model:

$$BRAC_t = \alpha_0 + \alpha_1 BRAC_{t-1} + \alpha_2 WD_{t-1} + \varepsilon_t \quad (3)$$

$$WD_t = \beta_0 + \beta_1 WD_{t-1} + \beta_2 BRAC_{t-1} + \mu_t, \quad (4)$$

[12] Analysis at the person-level was not possible in this test because of the lack of person-level longitudinal data.
[13] Worker density is the number of workers per square kilometer. We define a "worker" as one who works for someone else for wages, salary, piece rate, commission, tips, or payments "in kind" (for example, food or lodging received as payment for work performed); works in his or her own business, professional practice, or farm; performs any work in a family business or farm, paid or not; performs any part-time work including babysitting, paper routes, etc.; and/or is active duty in the Armed Forces.

where $BRAC_t$ is the change in the number of military individuals in the 2005 BRAC and WD_t is the worker density (in workers/km^2). We then test for Granger causality in each of the 136 PUMAs.

Applying the Bonferroni correction to adjust for multiple hypothesis testing (Bland and Altman, 1995; Napierala, 2012), we find that worker density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC at a 5% level in all but 7% of the 136 PUMAs with military bases. We therefore find evidence that worker density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC.

We also conduct a third Granger causality test to test whether train density, an indicator of the transportation system, Granger-caused the change in the number of military individuals in the 2005 BRAC. We test for Granger causality in each of the 136 PUMAs that have military bases. For each of the 136 PUMAs, we first estimate the following VAR model:

$$BRAC_t = \alpha_0 + \alpha_1 BRAC_{t-1} + \alpha_2 TD_{t-1} + \varepsilon_t \tag{5}$$

$$TD_t = \beta_0 + \beta_1 TD_{t-1} + \beta_2 BRAC_{t-1} + \mu_t, \tag{6}$$

where $BRAC_t$ is the change in the number of military individuals in the 2005 BRAC and TD_t is the train density (in train workers/km^2). We then test for Granger causality in each of the 136 PUMAs.

Applying the Bonferroni correction to adjust for multiple hypothesis testing (Bland and Altman, 1995; Napierala, 2012), we find that train density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC at a 5% level in all but 5% of the 136 PUMAs with military bases. We therefore find strong evidence that train density did not significantly Granger-cause the change in the number of military individuals in the 2005 BRAC, which lends further support for the exogeneity of the 2005 BRAC.

6. Difference-in-Difference-in-Differences Estimation

The first approach we use to explore the relationship between employment growth shocks and change in travel time is to estimate difference-in-difference-in-differences (DDD) models (Gruber, 1994; Kellogg and Wolff, 2008) with geographic and year fixed effects and a vector of control variables. DDD models measure the impact of an intervention or policy by comparing the treated group to two control groups both before the policy and after the policy.

In our DDD models, the policy we consider is the 2005 BRAC. We estimate the impact of the BRAC-related employment growth on military commuters using military personnel in BRAC-affected PUMAs as the treatment group. A dummy variable is used to distinguish between the pre-BRAC period (2000 and 2005) and post-BRAC period (2006-2010).

We distinguish between BRAC-affected PUMAs and non-BRAC-affected PUMAs. A "BRAC-affected PUMA" is a PUMA with one of the 57 bases that received troops in the 2005 BRAC. A "non-BRAC-affected PUMA" is a PUMA with one of the 36 bases not affected by the 2005 BRAC.

An "adjacent PUMA" is a PUMA that is adjacent to either one of the 57 BRAC-affected PUMAs, or one of the 36 non-BRAC-affected PUMAs. For each of the 57 BRAC-affected PUMAs and 36 non-BRAC-affected PUMAs, we select the adjacent PUMA that seemed to be the best control for the base PUMA (i.e., similar population density), from among all PUMAs adjacent to the base PUMA.

We estimate two different DDD models, DDD-1 and DDD-2, as described below. Both DDD models use two control groups. In each model, we estimate both an "all commuters" specification that uses data from all commuters, and a "drivers-only" specification that restricts the sample to those who commute by driving. The "all commuters" specification allows for the possibility that the 2005 BRAC and its resulting increase in congestion may have increased the travel time to work for commuters that did not drive to work, including, for example, those who may have taken a bus to work.

In the DDD-1 model, one control group we use consists of civilians who work in BRAC-affected PUMAs but do not work on base. This enables us to difference away any shocks to BRAC-affected PUMAs that affect both the military and the civilians in these communities, as well as any pre-existing differences in travel time between the military and civilians in these BRAC communities. Using Figure 2 as an illustration, DD-1 compares the military members who commute in the BRAC-affected PUMA in which Fort Meade is located (represented by the dark grey area surrounding Fort Meade) with civilians who work in the same BRAC-affected PUMA.

The advantage of using civilians who work in BRAC-affected PUMAs but do not work on base as a control group is that both treatment and control groups share the same geographic area, and therefore have similar land-use and transportation infrastructure. However, the disadvantage of this treatment group is that these civilians are also affected by increased traffic congestion caused by the troop re-locations since they work in the vicinity of a BRAC-affected base. If this is true, however, it would mean a significant effect would be more difficult to detect. The second disadvantage is that, as civilians, this control group may not be exposed to any changes in policies, traffic regulations, or infrastructure specific to military bases, and thus does not enable us to control for them.

To address the disadvantages of the first control group, a second control group the DDD-1 model uses consists of the military commuters in non-BRAC-affected PUMAs. This control group is not affected by increased traffic congestion caused by the troop re-locations. This control group enables us to difference away any shocks to military bases that affect the military on both BRAC-affected PUMAs and non-BRAC-affected PUMAs, as well as any pre-existing differences in travel time between the military on BRAC-affected PUMAs and the military on non-BRAC-affected PUMAs. Again with Figure 2 as an example, this control group enables us to compare travel time of military commuters on Fort Meade with military commuters at Fort AP Hill.

The advantage of using military commuters in non-BRAC-affected PUMAs as a control group is that it controls for military-specific factors that affected commute travel in the years 2000-2010. The disadvantage of this control group is that these individuals may be influenced by different set of city-level factors such as land-use, weather, transit availability, etc. since these bases are located in different regions. These disadvantages are addressed by the first control group, civilians who work in BRAC-affected PUMAs.

By using both civilians who work in BRAC-affected PUMAs and the military commuters in non-BRAC-affected PUMAs as our two control groups, our DDD-1 model addresses the disadvantages that arise from using either control group alone. In particular, our DDD-1 model differences out both changes in travel time experienced by civilians in the BRAC communities as well as changes in travel time experienced by military individuals on non-BRAC affected bases. The control structure of our DDD-1 model is therefore threefold:

(i) Cross-sectional over PUMAs (with BRAC-affected PUMAs as the treated PUMA and non-BRAC-affected PUMAs as the control)

(ii) Temporal over years (with the pre-BRAC years in BRAC-affected PUMAs and non-BRAC affected PUMAs as the control)

(iii) Cross-sectional within PUMAs (with civilians who work in BRAC-affected PUMAs as the "within-BRAC-affected PUMA" control)

Our DDD-1 model thus controls for factors that affect both military and non-military members in the same PUMAs as well as factors affecting military members on all bases, allowing us to identify the effect of the BRAC on the travel time of military members on BRAC-affected bases.

The DDD-1 model is given by:

$$TT_{irt} = \alpha + \beta_1 post_t + \beta_2 military_{irt} + \beta_3 BRAC_{affected_r} + \beta_4 post * military_{irt} + \beta_5 post * BRAC\_affected_{rt} + \beta_6 military * BRAC\_affected_{irt} + \delta post * military * BRAC\_affected_{irt} + \varphi_r + \theta_t + X_{irt}'\gamma + \varepsilon_{irt} \quad , \tag{7}$$

where TT_{irt} is the log one-way commute travel time of individual *i* in PUMA *r* in year *t*; α is a constant; $post_t$ is a dummy variable for post-2005; $military_{irt}$ is a dummy for individual *i* in PUMA *r* in year *t* being military personnel; $BRAC\_affected_r$ is a dummy for PUMA *r* being a BRAC-affected PUMA; $post*military_{irt}$ is a dummy for military personnel after 2005; $post*BRAC\_affected_{rt}$ is a dummy for military or civilians who live in a BRAC-affected PUMA after 2005; $military*BRAC\_affected_{irt}$ is a dummy for military personnel in BRAC-affected PUMAs; $post*military*BRAC\_affected_{irt}$ is the interaction term of interest for military personnel who live in the BRAC-affected PUMAs in years after 2005; φ_r are state fixed effects; θ_t are year fixed effects; and X is a vector of control variables. The difference-in-difference-in-difference estimator is δ, the coefficient on the $post*military*BRAC\_affected_{irt}$ interaction.

We use the following individual-level control variables: age, age squared, education, a dummy for being female, a dummy for being married, a dummy for having immigrated to the US, hours worked per week, family income, number of vehicles per adult in household, family size, and number of children. We also use the following PUMA-level control variables: lagged average commute travel time in the PUMA, bus density (bus workers/km^2), train density (train workers/km^2), a dummy for living in an urban area, a dummy for living in a rural area, bus density of workplace (bus workers/km^2), and train density of workplace (train workers/km^2).

The coefficient of interest is δ, the coefficient on the $post*military*BRAC\_affected_{irt}$ interaction, as it is the difference-in-difference-in-difference estimator. The interpretation of this coefficient is the additional one-way commute travel time (in minutes) for the treatment group associated with the 2005 BRAC.

So that the standard errors are robust to both arbitrary heteroskedasticity and arbitrary intra-group correlation, we cluster the standard errors by household.

In our DDD-2 model, instead of using civilians who work in BRAC-affected PUMAs but do not work on base as one of our control groups, we instead use civilian commuters in adjacent PUMAs as a control group. In Figure 2, this control group works in the black "adjacent" PUMA that is adjacent to the BRAC-affected PUMA in which Fort Meade is located. Using civilian commuters in adjacent PUMAs as a control group enables us to difference away any regional shocks that affect the military and civilians in both BRAC-affected PUMAs and their adjacent PUMAs, as well as any pre-existing differences in travel time between the military and civilians on BRAC-affected PUMAs and the military and civilians on adjacent PUMAs. The hope is that choosing reference groups that are geographically adjacent to BRAC-affected PUMAs controls for built environment variables.

As in DDD-1, a second control group the DDD-2 model uses consists of the military commuters in non-BRAC-affected PUMAs. This ensures the control group is not affected by increased traffic congestion caused by the troop re-locations. This control group enables us to difference away any shocks to military bases that affect the military on both BRAC-affected PUMAs and non-BRAC-affected PUMAs, as well as any pre-existing differences in travel time between the military on BRAC-affected PUMAs and the military on non-BRAC-affected PUMAs. Again with Figure 2 as an example, we therefore compare travel time of military commuters on Fort Meade with military commuters at Fort AP Hill.

By using both civilian commuters in adjacent PUMAs and the military commuters in non-BRAC-affected PUMAs as our two control groups, our DDD-2 model differences out both changes in travel time experienced by civilians in communities adjacent to the BRAC communities as well as changes in travel time experienced by military individuals on non-BRAC affected bases. The control structure of our DDD-2 model is threefold:

(i) Cross-sectional over PUMAs (with BRAC-affected PUMAs as the treated PUMA and non-BRAC-affected PUMAs, PUMAs adjacent to BRAC-affected PUMAs, and PUMAs adjacent to non-BRAC-affected PUMAs as the controls)

(ii) Temporal over years (with the pre-BRAC years in BRAC-affected PUMAs, non-BRAC affected PUMAs, PUMAs adjacent to BRAC-affected PUMAs, and PUMAs adjacent to non-BRAC-affected PUMAs as the control)

(iii) Cross-sectional within military (with military who work in non-BRAC-affected PUMAs as the "within-military" control)

The DDD-2 model thus controls for factors that affect both military individuals in BRAC-affected PUMAs and civilians in PUMAs adjacent to BRAC-affected PUMAs, as well as factors affecting military members on all bases, allowing us to identify the effect of the BRAC on the travel time of military members on BRAC-affected bases.

The DDD-2 model is given by:

$$TT_{irt} = \alpha + \beta_1 post_t + \beta_2 military_{irt} + \beta_3 gained_r +$$
$$\beta_4 post * military_{irt} + \beta_5 post * gained_{rt} + \beta_6 military * gained_{irt} +$$
$$\delta post * military * gained_{irt} + \varphi_r + \theta_t + X_{irt}'\gamma + \varepsilon_{irt} \quad , \qquad (8)$$

where TT_{irt} is the log one-way commute travel time of individual i in PUMA r in year t; α is a constant; $post_t$ is a dummy variable for post-2005; $military_{irt}$ is a dummy for individual i in PUMA r in year t being military personnel; $gained_r$ is a dummy for PUMA r being a BRAC-affected PUMA or a PUMA adjacent to a BRAC-affected PUMA; $post*military_{irt}$ is a dummy for military personnel after 2005; $post*gained_{rt}$ is a dummy for military or civilians who live in a BRAC-affected PUMA or a PUMA adjacent to a BRAC-affected PUMA after 2005; $military*gained_{irt}$ is a dummy for military personnel in BRAC-affected PUMAs; $post*military*gained_{irt}$ is the interaction term of interest for military personnel who live in the BRAC-affected PUMAs in years after 2005; φ_r are state fixed effects; θ_t are year fixed effects; and X is the same vector of control variables used for DDD-1. The difference-in-difference-in-difference estimator is δ, the coefficient on the $post*military*gained_{irt}$ interaction.

Summary statistics for all the treatment and control groups in the two DDD models are provided in Table A1 in Appendix A.

Two main conditions are required in order for the DDD estimator to be unbiased. The first is that the time effects θ_t must be common across treated and untreated individuals

(Cameron and Trivedi, 2005; Blundell and MaCurdy, 1999). To examine this assumption, Figure 3 plots the one-way commute time for the treatment group and each control group.

As seen in Figure 3, the military in BRAC-affected PUMAs treatment group and the non-BRAC-affected PUMA military control group exhibited parallel trends prior to the BRAC treatment, which suggests that our use of this control group controls for past trends in the military treatment group. Both our DDD models use this non-BRAC-affected PUMA military group as a control group.

A second condition that is required in order for the DDD estimator to be unbiased is that the treatment must be exogenous to unobserved drivers of the outcome variables of interest (Wooldridge, 2002; Besley and Case, 2000; Jardine, Lin and Sanchirico, 2014). As we argued in Section 3, and evidenced by our Granger causality tests in Section 5, conditional on the control variables – which include train density, bus density, whether the area is urban, whether the area is rural, lagged average commute travel time in the area, state fixed effects, and year effects – the troop movements in the 2005 BRAC were exogenous to employment growth; and conditional on the control variables, omitted variables bias pose less of a concern.

However, for our DDD estimates of the treatment on the treated, we do not need the 2005 BRAC to be as good as randomly assigned. In other words, for our estimates of the effects of the 2005 BRAC on travel time, random treatment is not required.

Table 4 shows the results of our DDD-1 and DDD-2 models. Results of the DDD estimator δ show that the employment growth of the 2005 BRAC is associated with a 16.9 to 19.9 percent increase in travel time per one-way commute trip for military commuters. We estimate economic costs associated with the increased travel times in Section 8.

To better understand whether the magnitude of these variations in travel time are large or small, we compared our results to the variation in travel time to work across years for a given PUMA (within) and across PUMAs for a given year (between) presented in Table 3. The within-group standard deviations of 1.30 and 1.46 for all PUMAs in the U.S. and for the BRAC-affected PUMAs, respectively, represent 5.2 percent and 6.4 percent of the respective means. The between-group standard deviations of 5.28 and 4.82 for all PUMAs in the U.S. and for the BRAC-affected PUMAs, respectively, represent 21.0 percent and 21.2 percent of the respective means. Thus, the effect of the employment growth of the 2005 BRAC on commute travel time for military commuters is roughly 3 to 4 times higher than the variation in travel time to work across years for a given PUMA; and almost as high as the variation in travel time to work across PUMAs for a given year.

An advantage of the DDD approach is that for our DDD estimates of the treatment on the treated, we do not need the 2005 BRAC to be as good as randomly assigned. In other words, for our estimates of the effects of the 2005 BRAC on travel time, random treatment is not required. However, a disadvantage of the DDD approach is that it only enables us to estimate the effect of the 2005 BRAC on travel time to work, but does not control for any induced changes in civilian employment. Owing to this disadvantage of the DDD model, we now turn to our preferred approach, our instrumental variable (IV) approach, in which we instrument for employment density using change in military troops under the 2005 BRAC and therefore isolate the exogenous component of the employment growth from any endogenous employment feedback, whether positive or negative.

7. Instrumental Variable Estimation

Our second, and preferred, approach to estimating the effect of worker density on travel time to work uses the change in military troops in the 2005 BRAC as an instrument for worker density.[14] The change in the number of military individuals in the 2005 BRAC is a good instrument because it is related to worker density but in the short run it is unrelated to travel time to work except through the endogenous variable. This exogeneity was discussed in Section 3, and further evidence was provided by the Granger causality tests in Section 5.

The IV approach has several advantages over the DDD approach. By using an instrument for worker density, we isolate the exogenous component of the employment growth from any endogenous employment feedback, whether positive or negative, and therefore control for any induced changes in civilian employment. Our IV method thus enables measurement of a causal relationship between employment density and travel time. Moreover, unlike the DDD models, which can only identify the effect of the 2005 BRAC, our IV models identify the effect of worker density on travel time, and therefore has external validity beyond the 2005 BRAC.

The IV model is:

$$TT_{irt} = \alpha + \beta_1 WD_{rt} + \varphi_r + \theta_t + X_{irt}'\gamma + \varepsilon_{irt} \,, \quad (9)$$

where TT_{irt} is the log one-way commute travel time to work for individual *i* in PUMA *r* at time *t*; WD_{rt} is the worker density (workers/km^2) of PUMA *r* at time *t*; φ_r are state-level fixed effects, θ_t are year fixed effects, X_{irt} is the same vector of control variables as in the DDD models, and

[14] Worker density is the number of workers per square kilometer. We define a "worker" as one who works for someone else for wages, salary, piece rate, commission, tips, or payments "in kind" (for example, food or lodging received as payment for work performed); works in his or her own business, professional practice, or farm; performs any work in a family business or farm, paid or not; performs any part-time work including babysitting, paper routes, etc.; and/or is active duty in the Armed Forces.

ε_{irt} is the disturbance term. We instrument for worker density WD_{rt} using the change in the number of military individuals in the 2005 BRAC.

As in the DDD models, we use the following individual-level control variables: age, age squared, education, a dummy for being female, a dummy for being married, a dummy for having immigrated to the US, hours worked per week, family income, number of vehicles per adult in household, family size, and number of children. We also use the following PUMA-level control variables: lagged average commute travel time in the PUMA, bus density (bus workers/km^2), train density (train workers/km^2), a dummy for living in an urban area, a dummy for living in a rural area, bus density of workplace (bus workers/km^2), and train density of workplace (train workers/km^2).

So that the standard errors are robust to both arbitrary heteroskedasticity and arbitrary intra-group correlation, we cluster the standard errors by household. We are unable to cluster the standard errors by PUMA because there would be too few clusters in our military-only regressions. Cluster-robust standard errors require the assumption that the number of clusters, rather than just the number of observations, goes to infinity. If there are too few clusters, the estimated residuals will systematically be too close to zero compared to the true error terms, leading to a downwards-biased cluster-robust variance matrix estimate. Thus, when there are too few clusters, test statistics based on the cluster-robust standard errors over-reject and confidence intervals are too narrow (Cameron and Miller, 2015).

When each cluster has the same number of observations, then the current consensus is that a minimum of 50 clusters is needed in order to cluster standard errors, although the more clusters the better. However, when the number of observations varies by cluster, then the minimum number of clusters needed is higher (Cameron and Miller, 2015).

Cameron, Gelbach and Miller (2011) find that when there are 10 clusters and the number of observations varies by cluster, the rejection rate is worse than the rejection rate when there are 100 clusters of equal size (Cameron and Miller, 2015). Carter, Schnepel and Steigerwald (2013) and Imbens and Kolesar (2012) provide theory that indicates that the effective number of clusters is reduced when the number of observations varies across clusters; see also the simulations in MacKinnon and Webb (forthcoming).

Carter, Schnepel and Steigerwald (2013) find that with 100 clusters, if the largest cluster has 4.96 times more observations than it would have if the 100 clusters were of equal size, then the effective number of clusters is approximately 20-65% of the actual number of clusters, depending on the degree of heteroskedasticity; if the largest cluster has 8.96 times more observations than it would have if the clusters were of equal size, then the effective number of clusters is approximately 5-30% of the actual number of clusters, depending on the degree of heteroskedasticity.

Our largest BRAC-affected PUMA has 7.51 more observations than it would have if the BRAC-affected PUMAs were of equal size. As the effective number of clusters is likely between 5% and 65% of the number of clusters (Carter, Schnepel and Steigerwald, 2013), if we clustered our military-only regressions by PUMA, with 57 BRAC-affected PUMAs our effective number of clusters would likely be between 2.85 and 37.50 clusters. Thus, the effective number of clusters would therefore likely be far less than the minimum of 50 effective clusters needed in order to be able to cluster the standard errors. As a consequence, so that the standard errors are robust to both arbitrary heteroskedasticity and arbitrary intra-group correlation, we cluster the standard errors by household instead.

For our IV models, “adjacent PUMAs” are PUMAs adjacent to a military base. For each PUMA with a military base, we select the adjacent PUMA that seemed to be the best control for the base PUMA (i.e., similar population density), from among all PUMAs adjacent to the PUMA with the military base. As there are 57 BRAC-affected base PUMAs that gained troops, 43 BRAC-affected base PUMAs that lost troops, and 36 base PUMAs that did not gain or lose troops, for a total of 136 PUMAs with military bases, there are 136 adjacent PUMAs.

Summary statistics for the data used in the IV models for the military and the civilians are presented in Table A2 in Appendix A.

Tables 5a and 5b present the results of the first-stage regressions for the military-only models and the civilian-only models, respectively. The first-stage F-statistics are all quite large, and all much larger than 10. Moreover, we pass the underidentification tests and weak-instrument-robust inference tests as well.

The dependent variable in our first-stage regressions is our endogenous variable, worker density (workers/km^2). In specifications (1) and (2) of both Tables 5a and 5b, the coefficient on our instrument, the change in the number of military individuals in the 2005 BRAC, is significant and negative. As we use annual data and as our data set extends a few years after the 2005 BRAC, the relevant time horizon for the “short run” that we use in this paper is on the order of a year to a few years. Even in the short run, it is possible that some people may respond to employment growth by moving. Our estimates in specifications (1) and (2) of both tables therefore measure the short-run effect of employment growth after individuals have had a chance to respond by moving. The negative sign on the instrument therefore suggests that the short-run effect of employment growth from the 2005 BRAC on worker density after individuals have had a chance to respond by moving is negative.

Specifications (3) and (4) of Tables 5a and 5b repeat specifications (1) and (2) of the respective table, using all the same variables and the same values of the variables including the same dependent variable and the same instrument, but this time restricting the respective sample used in the regression to only individuals who have lived in the same house since before 2005. These specifications enable us to examine the effects of the employment growth resulting from the 2005 BRAC on the individuals who were already in the area and did not move. Since a possible response to an increase in employment growth is to move, restricting our sample to those who did not move enables us to estimate a very short-run effect of employment growth, before individuals have a chance to respond by moving. The coefficient on the instrument is significant and positive in specifications (3) and (4) of Tables 5a and 5b, which suggests that the very short-run effect of employment growth from the 2005 BRAC on worker density before individuals have a chance to respond by moving is positive.

The results of eight IV models are shown in Tables 6a and 6b. We run specifications for both military and civilian subgroups, for drivers and for all commuters.

According to the results in Table 6a, an increase in worker density in workers per square kilometer of 1 percent increases the travel time to work for those in the military by 11.16 to 11.83 percent. According to the results in Table 6b, an increase in worker density in workers per square kilometer of 1 percent increases the travel time to work for civilians by 4.99 to 10.57 percent. We estimate the economic costs of the increased travel time in Section 8.

To better understand whether the magnitude of these variations in travel time are large or small, we compared our results to the variation in travel time to work across years for a given PUMA (within) and across PUMAs for a given year (between) presented in Table 3. The within-group standard deviations of 1.30 and 1.46 for all PUMAs in the U.S. and for the BRAC-affected

PUMAs, respectively, represent 5.2 percent and 6.4 percent of the respective means. The between-group standard deviations of 5.28 and 4.82 for all PUMAs in the U.S. and for the BRAC-affected PUMAs, respectively, represent 21.0 percent and 21.2 percent of the respective means. Thus, the effect of an increase in worker density in workers per square kilometer of 1 percent on commute travel time for military commuters is roughly 2 times higher than the variation in travel time to work across years for a given PUMA; and more than half the variation in travel time to work across PUMAs for a given year. The effect of an increase in worker density in workers per square kilometer of 1 percent on commute travel time for civilian commuters roughly 1 to 2 times higher than the variation in travel time to work across years for a given PUMA; and roughly a quarter to half the variation in travel time to work across PUMAs for a given year.

To provide some intuition for our results, we apply our results to a sample of moderately sized cities with approximately 100,000 workers, and examine the effects of an increase in employment of 1000 workers on the commute travel time in these cities. The sample cities we chose, which all have approximately 100,000 workers, are: Tuscaloosa, Alabama; Greely, Colorado; Athens, Georgia; Binghamton, New York; and Laredo, Texas. According to the results in Table 7, an increase in employment of 1000 workers causes an increase in commute travel time of 10.00 to 11.55 percent for all commuters and 4.75 to 5.49 percent for drivers only in the sample of moderately sized cities with approximately 100,000 workers.

It is possible that the increase in commute travel time for military individuals as a result of 2005 BRAC was because the new military that moved to the area due to the 2005 BRAC had to live further away than the military already in the area, and therefore had a higher commute travel time. To control for changes in travel distances following the BRAC, we also run robustness checks of our military-only models using only military individuals who have lived in the same house since before 2005. For the military-only models, restricting the sample to only individuals who have lived in the same house since before 2005 would enable us to examine the effects of the employment growth resulting from the 2005 BRAC on the military individuals who were already in the area and did not move.

According to the results in Table 8a, restricting the sample to only military individuals who have lived in the same house since before 2005 results in a lower elasticity of worker density with respect to commute travel time, but the elasticity is still significant and positive in BRAC-affected PUMAs.[15] An increase in worker density in workers per square kilometer of 1 percent increases the travel time to work for those in the military in BRAC-affected PUMAs who were already in the area and did not move by 3.89 to 4.56 percent.

We also run similar robustness checks for the civilian-only models using only civilian individuals who have lived in the same house since before 2005. For the civilian-only models, restricting the sample to only individuals who have lived in the same house since before 2005 would enable us to examine the effects of the employment growth resulting from the 2005 BRAC on the civilian individuals who were already in the area and did not move. Since a possible response to an increase in employment growth is to move, restricting our sample to those who did not move enables us to estimate a very short-run effect of employment growth, before individuals have a chance to respond by moving.

According to the results in Table 8b, restricting the sample to only civilian individuals who have lived in the same house since before 2005 results in a higher elasticity of worker

[15] While the elasticity is also significant and positive for drivers only in BRAC-affected PUMAs and adjacent PUMAs, the positive elasticity is not significant for all commuters in BRAC-affected PUMAs and adjacent PUMAs, possibly because our first-stage F-statistic was too low for that model. As we were unable to find a strong instrument for this latter model, we focus instead on the results for BRAC-affected PUMAs.

density with respect to commute travel time. An increase in worker density in workers per square kilometer of 1 percent increases the travel time to work for civilians who were already in the area and did not move by 9.54 to 31.71 percent. Thus, the very short-run effect of employment growth on commute travel time can be quite high, and is higher than the short-run effect of employment growth after individuals have had a chance to respond by moving.

In addition to our IV regressions of log one-way commute travel time, we also run a set of IV regressions to examine the effect of employment growth on commute departure time and on commute arrival time. Our analysis and results are presented in Appendix B. According to our results in Tables B2 and B3 in Appendix B, we find some evidence that employment growth may cause civilian commuters to both depart from home later and to arrive at work later, at least for commuters in BRAC-affected PUMAs. In addition, according to our results in Tables B4 and B5 in Appendix B, we find evidence that employment growth causes military commuters to both depart from home earlier and to arrive at work earlier.

8. Economic Costs of Travel Time

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

We use Litman's method to obtain a back-of-the-envelope estimate of the short-run travel time costs from the 2005 BRAC. Over the period 2006-2010, the average income of military individuals at the BRAC-affected bases was $43,755 per year (in constant 2005 dollars) or $17.53 per hour worked (Ruggles et al., 2015).[16] Under Litman's framework, each additional man-hour stuck in traffic congestion results in a cost of $8.77 to $17.53 per military commuter. We combine these statistics with the results of our DDD and IV models to calculate the total cost of the 2005 BRAC to military commuters and to civilian commuters.

Results from our travel time cost calculations are summarized in Tables 9 and 10. We use the highest and lowest estimates from the DDD models in Table 4 and the highest and lowest estimates from the IV models in Tables 6a and 6b. We present the range of estimates for each method using 0.5 and 1.0, respectively, for wage rate multipliers.

Using the range of coefficients estimated in the DDD and IV models, the total short-run congestion cost of the 2005 BRAC for all military in BRAC-affected PUMAs due to increased commuting time is $79 to $761 million per year (in constant 2005 dollars).[17] Applying the same calculations to the civilians workers' average wage rate of $25.02 per hour, we estimate the total short-run congestion cost of the 2005 BRAC for all civilians in BRAC-affected PUMAs due to increased commuting time to be $3.15 to $6.30 billion per year (in constant 2005 dollars). For

[16] This estimate relies on two variables from Ruggles et al. (2015): *average hours worked per week* and *weeks worked per year.*
[17] For the IV model, we calculated that on average, BRAC-affected PUMAs added 116 new workers per square kilometer due to the 2005 BRAC. When multiplied by the IV regression coefficients and evaluated at mean travel time, this gives the additional minutes of travel time from the 116 workers per square kilometer.

comparison, Anderson (2014) estimates the congestion relief benefit of operating public transit in Los Angeles given the current road network is $1.2 to $4.1 billion per year.

In Table 11, we make similar calculations for the U.S. general employed population using the IV coefficients in the civilian models for all U.S. PUMAs in Table 6b and the estimated U.S.-wide wage rate. Use of DDD coefficients is not possible for the U.S.-wide effect. We find that each additional 10 workers added to the transportation network per square kilometer adds 0.171 to 0.244 additional minutes of travel per commuter per one-way commute trip in the short run, which equates to $0.07 to $0.20 of travel time cost per commuter per day.

It should be noted that Downs (2004) and others express concern about simple travel time value calculations based on wage rate because no two people experience the same cost and some even report a net benefit from added travel time. However, for the purposes of this study, such a calculation provides a convenient back-of-the-envelope quantification of the burden imposed by the BRAC and employment growth in general. We find the calculation useful for comparison with other costs and benefits of employment growth. For example, our estimates for the total cost of the 2005 BRAC to civilian commuters due to increased commuting time are $3.15 to $6.30 billion per year (in constant 2005 dollars), while the DoD estimated that the 2005 BRAC would provide $37 billion in *savings* over ten years in reduced manpower and infrastructure costs. Like most such estimates, the DoD valuation of BRAC does not consider the cost of added travel time.

9. Conclusion

Employment growth is a common public policy goal, but it can lead to a number of unwanted environmental, social, and economic costs – particularly in high growth communities –

due to its impact on peak-hour traffic. When policy-makers craft legislation for job growth, they should work with transportation planners to mitigate negative impacts on traffic flow. To some extent, transportation networks are self-regulating (Litman, 2010) and in the long run added travelers will eventually find alternative routes, departure times, or modes to compensate for congested networks (Downs, 1992; Choo and Mokhtarian, 2008). While past research has shown that the total employment size of an area is positively correlated with travel time to work, our research is the first to our knowledge to empirically examine the effect of rapid employment growth on travel time.

Our results are quite robust – each additional 10 workers added to the transportation network per square kilometer adds 0.171 to 0.244 additional minutes of travel per commuter per one-way commute trip in the short run, which equates to \$0.07 to \$0.20 of travel time cost per commuter per day. We estimate the congestion cost of the 2005 BRAC to be \$79 to \$761 million per year (in constant 2005 dollars) for military commuters and \$3.15 to \$6.30 billion per year (in constant 2005 dollars) for civilian commuters.

A couple of specific qualifications should be mentioned regarding the data and the conclusions. Freight transportation is affected by increased congestion levels because delays in shipping will inevitably create economic burdens for freight firms, particularly those with perishable products. Due to lack of the necessary freight transport data, this cost is not measured here but we can only assume it is a positive cost. Also, considerable heterogeneity exists between cities in their spatial structure, transit availability, transportation policy, natural barriers to travel, and demographic composition. The findings in this study are "average effects" and asymmetric responses between communities are likely. Additionally, adding military members to a community may have a different effect on travel times than adding a similar number of civilian workers. Military commuters have a slightly higher tendency to drive to work and to drive alone (Morrison and Lin Lawell, 2016; Ruggles et al., 2015). Lastly, some of the increases in travel time measured above could be due to increases in distance of travel, not congestion. However, because the announcement about base realignments in the 2005 BRAC occurred abruptly and because of myriad media accounts of increased congestion due to BRAC, we argue that the majority of the increases in travel time due to BRAC were likely congestion-related, not distance-related.

While congestion may have a number of adverse effects, including discouraging future economic growth (Hymel, 2009; Sweet, 2011), increasing vehicular emissions, increasing fuel expenses, increasing operating costs for both private and freight vehicles, decreasing economies of agglomeration, heightening the psychological burden of travel, creating a need for more emergency services, decreasing the reliability of travel, and imposing an opportunity cost on time (Downs, 1992; Downs, 2004; Brownstone and Small, 2005; Beaudoin, Farzin and Lin Lawell, 2015; Beaudoin, Farzin and Lin Lawell, 2016; Beaudoin and Lin Lawell, 2016b), our travel time cost calculations focus on the opportunity cost on time. Our cost estimates are therefore potentially a lower bound to the total costs of the increase in congestion due to employment growth, which may include some of the other costs of congestion as well.

Major fluctuations in the number of troops at domestic bases are expected in the next decade because of: 1) reductions to the Department of Defense's budget, 2) the return of many troops from foreign bases, and 3) another round of base closures expected in 2015. This paper has relevance for both transportation planners who seek effective growth strategies and Department of Defense officials who seek to mitigate transportation impacts from troop movements and base closures. Our research is therefore of interest to academics, policy-makers, and business practitioners alike.

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Table 1: Timeline of 2005 BRAC Process

Date	Action
Dec. 28, 2001	Congress authorizes DoD to explore options for a 2005 BRAC
Dec. 23, 2003	BRAC base selection criteria published in Federal Register
Mar. 23, 2004	DoD provides troop inventories of all bases to Congress
Apr. 1, 2005	Congress appoints 8-member BRAC commission to oversee BRAC process
May 16, 2005	Secretary of Defense submits recommendations of base closures to BRAC commission
Sept. 8, 2005	BRAC commission provides recommendations for realignments to Congress
Nov. 7, 2005	President approves BRAC base realignment list
Jan. 1, 2006	Troop relocations begin
Sept. 30, 2011	Deadline for completion of troop movements

Figure 1: BRAC-affected military bases that received troops (DoD, 2005-2010)

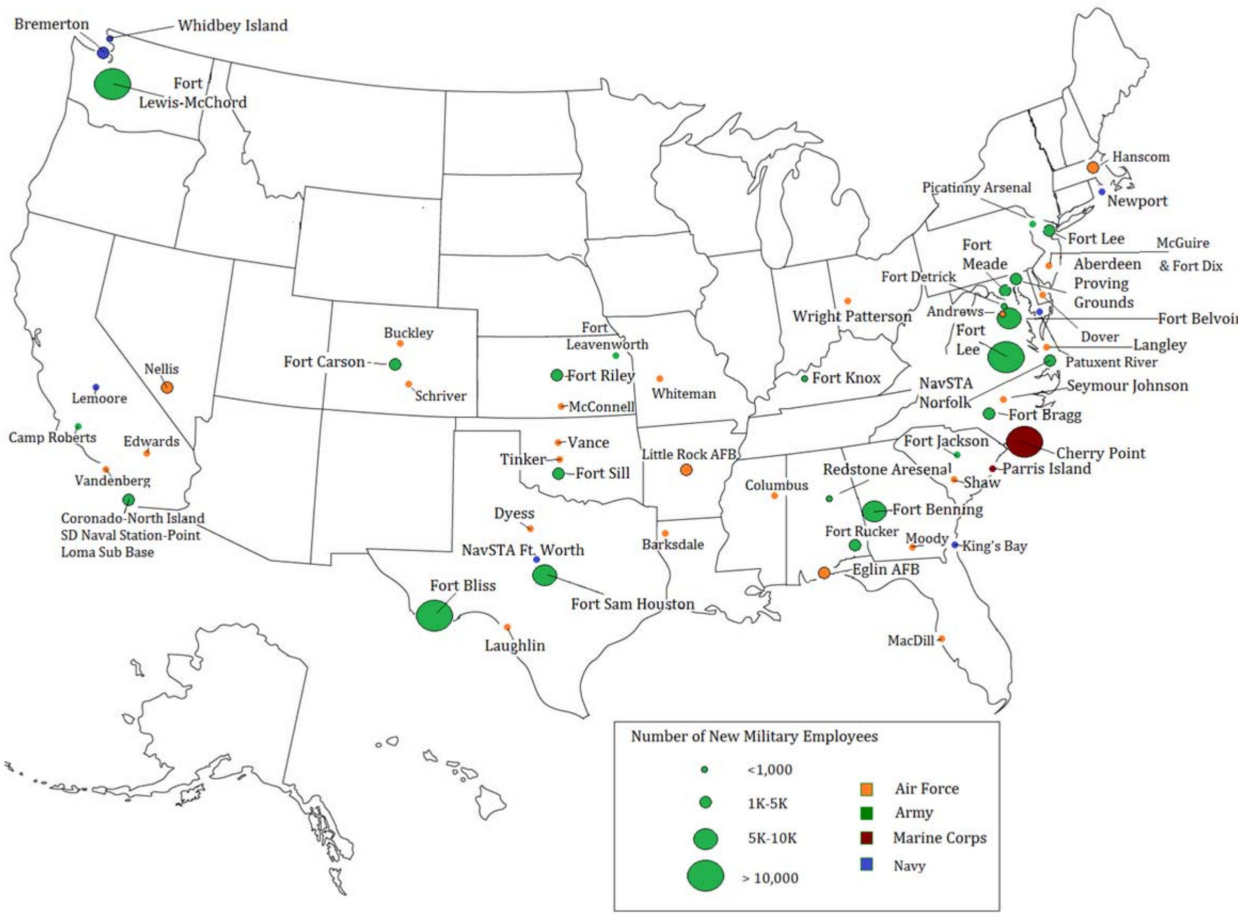

Table 2: Summary statistics

Variable	Min	Max	Military in BRAC-affected PUMAs *Mean (std dev)*	U.S. [1] *Mean (std dev)*[1]
One-way commute travel time (minutes), 2000-2005	0	172	17.7 (18.80)	23.81 (23.17)
One-way commute travel time (minutes), 2006-2010	0	188	18.1 (18.43)	23.58 (22.13)
Worker density (workers/km^2)	1.21	80079	2043.7 (4763)	2040.3 (497.40)
Age (yrs)	17	62	29.7 (8.35)	42.21 (13.80)
Family income ($10,000)	0	17.2	7.97 (7.33)[2]	16.5 (92.3)[2]
Education (yrs)	0	11	7.57 (1.83)	7.36 (2.31)
Female (dummy)	0	1	0.15 (0.36)	0.47 (0.50)
Vehicles per adult in household (number)	0	6	1.12 (0.71)	1.20 (0.72)
Family size (number)	0	31	2.40 (1.53)	2.84 (1.60)
Married (dummy)	0	1	0.71 (0.45)	0.53 (0.50)
Immigrated to US (dummy)	0	1	0.10 (0.29)	0.17 (0.37)
Hours worked per week (hrs)	0	99	50.15 (14.50)	39.46 (12.50)
Kids in household (number)	0	9	0.72 (1.08)	0.99 (0.70)
Train density (train workers/km^2)	0	0.36	0.015 (0.043)	0.32 (1.55)
Bus density (bus workers/km^2)	0.0	484.5	0.047 (0.090)	0.91 (3.62)
Lives in rural area (dummy)	0	1	0.16 (0.36)	0.15 (0.36)
Lives in urban area (dummy)	0	1	0.13 (0.34)	0.15 (0.36)
# Observations			20,162	9.60 million

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

Table 3: Within and between variation in one-way commute travel time, 2000-2010

	# Obs	Mean	Std Dev	Min	Max
All PUMAs in the U.S.					
Overall	14,482	25.19	5.42	6.67	71.2
Within			1.30	16.22	50.99
Between			5.28	8.22	47.75
BRAC-Affected PUMAs					
Overall	259	22.76	4.98	14.2	39.91
Within			1.46	18.36	35.78
Between			4.82	15.98	37.95

Notes: One-way commute travel time is in minutes. Within variation is the variation in one-way commute travel time across years for a given PUMA. Between variation is the variation in one-way commute travel time across PUMAs for a given year.

Figure 2: Examples of treatment and comparison groups in DDD models near Washington D.C. Military bases shown in red. Fort Meade received 3,297 new workers as a result of the 2005 BRAC (DoD, 2005-2010). Fort A.P. Hill neither received nor lost workers in the BRAC.

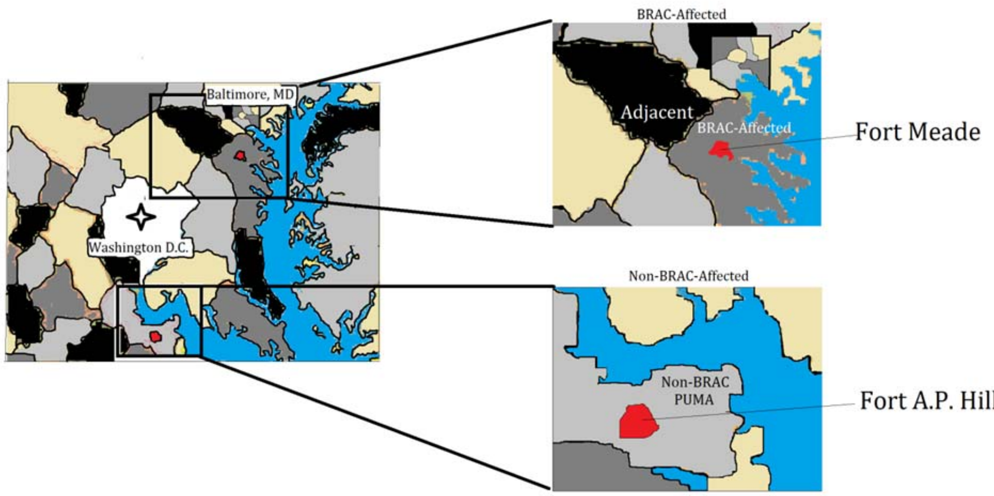

Figure 3: One-way commute travel times

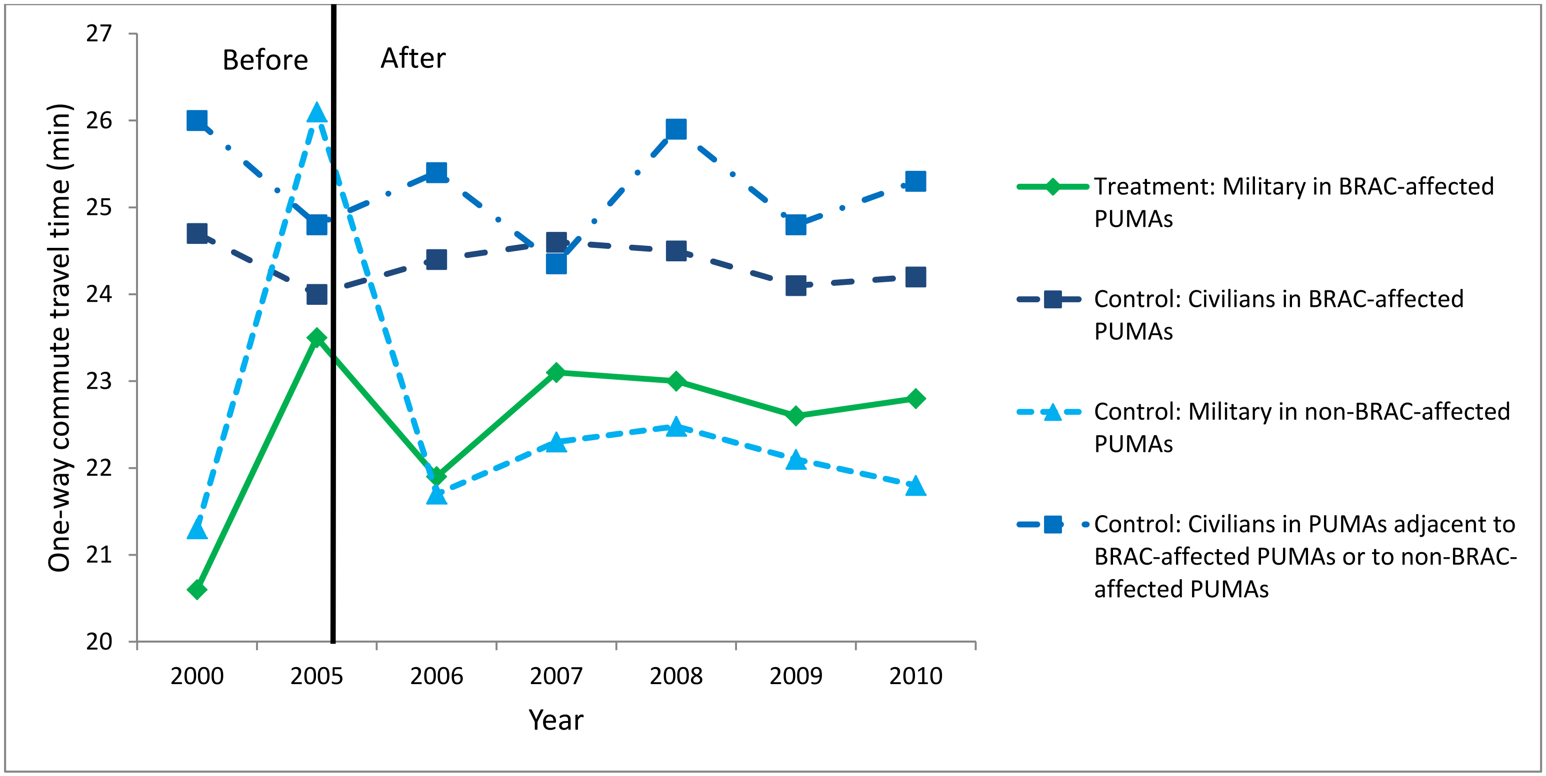

Table 4: Results of DDD models

	DDD-1		DDD-2	
	All Commuters	Drivers Only	All Commuters	Drivers Only
DDD Estimator	0.199**	0.173*	0.198**	0.169*
	(0.070)	(0.071)	(0.072)	(0.073)
Control Variables[ǂ]	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
Observations	230,698	218,630	511,471	484,819
R-squared	0.926	0.932	0.921	0.927

Notes: Standard errors clustered by household are in parentheses. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

[ǂ] We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table 5a: First-stage regressions for military-only models

	Dependent variable is worker density (workers/km^2)							
	(1)		(2)		(3)		(4)	
	Military-only		Military-only		Military-only		Military-only	
	BRAC-affected only		BRAC-affected only		BRAC-affected only		BRAC-affected only	
	All commuters		Drivers only		All commuters		Drivers only	
					Did not move		Did not move	
	Coef.	Std Error	Coef.	Std Error	Coef.	Std Error	Coef.	Std Error
Instrument								
Change in number of military individuals in 2005 BRAC	-0.0011***	(0.0003)	-0.0011***	(0.0002)	0.0112***	(0.0029)	0.0092***	(0.0023)
Individual								
Age (yrs)	-4.36	(3.51)	-6.50	(3.54)	-3.67	(4.91)	-2.98	(5.55)
Age squared (yrs^2)	0.06	(0.05)	0.08	(0.05)	0.04	(0.06)	0.01	(0.07)
Education (yrs)	7.706***	(2.20)	1.093	(1.95)	-1.333	(3.60)	-2.997	(3.50)
Female (dummy)	2.909	(10.30)	9.916	(9.78)	-43.98*	(17.28)	-39.09*	(17.56)
Married (dummy)	-27.4*	(12.29)	-17.9	(13.10)	-132.23*	(67.00)	-116.66	(66.98)
Immigrated to U.S. (dummy)	14.75	(12.13)	28.60*	(11.88)	19.02	(22.72)	19.09	(22.15)
Hours worked per week (hrs)	-0.01	(0.23)	-0.18	(0.20)	0.06	(0.42)	0.10	(0.39)
Family								
Family income ($10,000)	0.770***	(0.14)	0.625***	(0.15)	0.38	(0.22)	0.42	(0.22)
Vehicles per adult in household (number)	-14.3	(7.59)	-3.65	(7.32)	8.82	(12.31)	6.54	(12.35)
Family size (number)	-24.3**	(8.08)	-17.1	(9.07)	94.47	(50.26)	87.82	50.84
Kids in household (number)	16.15	(8.44)	14.46	(9.42)	-95.38	(52.13)	-88.69	(52.68)
Built Environment								
Lagged average one-way travel time to work (min)	2.906	(1.56)	0.781	(1.51)	6.85	(7.71)	4.88	(7.66)
Bus density (bus workers/km^2)	88.78***	(3.59)	96.24***	(5.73)	17.98	(17.06)	57.26	(38.58)
Train density (train workers/km^2)	65.05*	(25.34)	64.53*	(26.32)	158.99**	(55.26)	139.56**	(47.88)
Lives in urban area (dummy)	343.0***	(27.96)	376.9***	(24.52)	425.97***	(31.98)	426.41***	(33.57)

Lives in rural area (dummy)	-7.71	(4.46)	-3.97	(3.96)	-18.10	(10.79)	-16.73	(10.92)
Workplace bus density (bus workers/km^2)	-16.9	(10.29)	-24.7**	(7.51)	21.65	(11.59)	1.98	(17.03)
Workplace train density (train workers/km^2)	120.4***	(15.95)	114.7***	(13.80)	121.90***	(22.13)	124.38***	(21.88)
State fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Standard errors clustered by household	Yes		Yes		Yes		Yes	
First-stage F-statistic	15.82		31.56		14.86		16.44	
First-stage Shea Partial R-squared p-value	0.0006		0.0010		0.0106		0.0079	
Underidentification test p-value	0.0000		0.0000		0.0001		0.0000	
Weak-instrument-robust interference test p-value	0.0000		0.0000		0.0255		0.0233	
p-value(Pr>F)	0.0001		0.0000		0.0000		0.0000	
Observations	12,743		11,934		1,716		1,654	

Notes: Standard errors clustered by household are in parentheses. Specifications (3) and (4) limit the sample to individuals who lived in their house since at least 2005. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table 5b: First-stage regressions for civilian-only models

	Dependent variable is worker density (workers/km^2)							
	(1)		(2)		(3)		(4)	
	Civilian-only All USA All commuters		Civilian-only All USA Drivers only		Civilian-only All USA All commuters Did not move		Civilian-only All USA Drivers only Did not move	
	Coef.	Std Error	Coef.	Std Error	Coef.	Std Error	Coef.	Std Error
Instrument								
Change in number of military individuals in 2005 BRAC	-0.002***	(0.0001)	-0.002***	(0.0001)	0.0057***	(0.0004)	0.0055***	(0.0004)
Individual								
Age (yrs)	2.339***	(0.25)	2.520***	(0.22)	1.36**	(0.44)	1.31***	(0.40)
Age squared (yrs^2)	-0.03***	(0.003)	-0.03***	(0.003)	-0.02***	(0.005)	-0.02***	(0.005)
Education (yrs)	7.243***	(0.24)	5.693***	(0.21)	6.05***	(0.36)	4.94***	(0.31)
Female (dummy)	-1.51*	(0.76)	-1.85**	(0.66)	-1.83	(1.30)	-2.01	(1.13)
Married (dummy)	-26.1***	(1.05)	-22.5***	(0.93)	-34.13***	(2.19)	-29.72***	(1.98)
Immigrated to U.S. (dummy)	100.1***	(2.46)	89.84***	(2.24)	96.42***	(4.30)	88.89***	(4.00)
Hours worked per week (hrs)	0.41***	(0.04)	0.30***	(0.03)	0.14*	(0.058)	0.12*	(0.050)
Family								
Family income ($10,000)	0.26***	(0.01)	0.23***	(0.01)	0.34***	(0.03)	0.28***	(0.02)
Vehicles per adult in household (number)	-22.7***	(0.78)	-13.3***	(0.66)	-27.15***	(1.13)	-18.47***	(0.96)
Family size (number)	-10.9***	(0.73)	-6.36***	(0.65)	-7.28***	(1.63)	-3.78**	(1.45)
Kids in household (number)	2.11**	(0.79)	-0.54	(0.72)	0.98	(1.74)	-1.13	(1.57)
Built Environment								
Lagged average one-way travel time to work (min)	2.98***	(0.25)	2.03***	(0.21)	3.90***	(0.45)	2.69***	(0.35)
Bus density (bus workers/km^2)	33.56***	(0.96)	35.89***	(1.05)	32.73***	(1.46)	34.97***	(1.55)
Train density (train workers/km^2)	41.01***	(3.90)	37.00***	(3.84)	34.36***	(6.53)	30.35***	(5.13)
Lives in urban area (dummy)	548.1***	(5.02)	492.4***	(4.72)	551.01***	(8.76)	498.48***	(8.01)

	(1)		(2)		(3)		(4)	
Lives in rural area (dummy)	-42.0***	(0.75)	-48.0***	(0.73)	-42.68***	(1.17)	-48.63***	(1.05)
Workplace bus density (bus workers/km^2)	25.29***	(0.99)	25.11***	(1.16)	28.47***	(1.70)	28.42***	(1.98)
Workplace train density (train workers/km^2)	59.30***	(2.83)	52.82***	(2.73)	48.17***	(4.81)	43.27***	(4.30)
State fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
Standard errors clustered by household	Yes		Yes		Yes		Yes	
First-stage F-statistic	291.96		262.50		209.94		216.91	
First-stage Shea Partial R-squared p-value	0.0001		0.0001		0.0001		0.0001	
Underidentification test p-value	0.0000		0.0000		0.0000		0.0000	
Weak-instrument-robust interference test p-value	0.0000		0.0000		0.0000		0.0000	
p-value(Pr>F)	0.0000		0.0000		0.0000		0.0000	
Observations	2,916,175		2,771,243		1,073,031		1,025,549	

Notes: Standard errors clustered by household are in parentheses. Specifications (3) and (4) limit the sample to individuals who lived in their house since at least 2005.
Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

Table 6a: Results of IV models for military-only models

	Dependent variable is log one-way commute travel time (minutes)			
	Military Models			
	BRAC-affected PUMAs only		BRAC-affected PUMAs and adjacent PUMAs	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.007***	0.007***	0.007***	0.007***
	(0.0021)	(0.0016)	(0.0019)	(0.0015)
Elasticity	11.83***	11.38***	11.59***	11.16***
	(3.48)	(2.57)	(3.15)	(2.37)
Control variables‡	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	15.82	31.56	17.82	34.71
Observations	12,743	11,934	13,369	12,525

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

‡ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table 6b: Results of IV models for civilian-only models

	Dependent variable is log one-way commute travel time (minutes)			
	Civilian Models			
	BRAC-affected PUMAS only		All USA	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.001***	0.001***	0.0007***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Elasticity	6.35***	4.99***	10.57***	5.021***
	(1.26)	(1.12)	(2.61)	(0.92)
Control variables‡	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	429.59	396.96	291.96	262.50
Observations	255,196	242,003	2,916,175	2,771,243

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

‡ We use the following control variables:

- **Individual-level**: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children
- **PUMA-level:** lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table 7: Effect of 1000 additional workers on a sample of moderately sized cities with approximately 100,000 workers

	Tuscaloosa, AL	Greeley, CO	Athens, GA	Binghamton, NY	Laredo, TX
Data from IPUMS					
Employment (# workers)	103,000	102,000	91,500	105,700	100,200
Area (km^2)	172.8	77.7	306	28.9	233.4
Worker density (workers/km^2)	596	1,313	299	3,657	429
Effect of 1000 additional workers					
Change in worker density (workers/km^2)	5.8	12.9	3.3	34.6	4.3
Change in commute travel time (percent)					
All commuters	10.26%	10.36%	11.55%	10.00%	10.55%
Drivers only	4.87%	4.92%	5.49%	4.75%	5.01%

Table 8a: Results of IV models for military-only models restricting to individuals who lived in their house since at least 2005

	Dependent variable is log one-way commute travel time (minutes)			
	Military Models			
	BRAC-affected PUMAs only		BRAC-affected PUMAs and adjacent PUMAs	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.0023*	0.0028*	0.0039	0.0021*
	(0.0011)	(0.0013)	(0.0023)	(0.0009)
Elasticity	3.89 *	4.56 *	6.46	3.35*
	(1.86)	(2.12)	(3.81)	(1.44)
Control variablesǂ	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
Restrict to households who lived in their house since at least 2005	Yes	Yes	Yes	Yes
First-stage F-statistic	14.86	16.44	3.43	14.53
Observations	1,716	1,654	4,042	3,815

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

ǂ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table 8b: Results of IV models for civilian-only models restricting to individuals who lived in their house since at least 2005

	Dependent variable is log one-way commute travel time (minutes)			
	Civilian Models			
	BRAC-affected PUMAs only		All USA	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.0043 **	0.0036**	0.0021***	0.0019***
	(0.0014)	(0.0014)	(0.0002)	(0.0003)
Elasticity	27.31**	17.96*	31.71***	9.54***
	(8.89)	(6.99)	(3.02)	(1.51)
Control variables‡	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
Restrict to households who lived in their house since at least 2005	Yes	Yes	Yes	Yes
First-stage F-statistic	16.88	14.65	209.94	216.91
Observations	42,932	41,448	1,073,031	1,025,549

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

‡ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table 9: Calculations of travel time costs for military in BRAC-affected PUMAs

Military in BRAC-affected PUMAs	**DDD Calculations**	**IV Calculations**
Data from IPUMS		
Average income of military in BRAC-affected PUMAs ($2005)	$43,755	$43,755
Average hours worked per week by military in BRAC-affected PUMAs (hrs)	50.15	50.15
Average weeks worked per year by military in BRAC-affected PUMAs (wks)	49.78	49.78
Calculations		
Hourly income based on above ($/hr)	$17.53	$17.53
DDD estimator – low	0.169	
DDD estimator – high	0.199	
IV coefficient on worker density (workers/km^2) – low		0.007
IV coefficient on worker density (workers/km^2) – high		0.007
Total daily short-run cost of BRAC for all military in BRAC-affected PUMAs ($/day) – low	$319,063	$1,528,048
Total daily short-run cost of BRAC for all military in BRAC-affected PUMAs ($/day) – high	$751,402	$3,056,097
Total annual short-run cost of BRAC for all military in BRAC-affected PUMAs ($) – low	**$79,416,829**	**$380,341,631**
Total annual short-run cost of BRAC for all military in BRAC-affected PUMAs ($) – high	**$187,028,981**	**$760,683,261**

Note: The DDD estimators and IV coefficients are measured in terms added log travel time per added workers per square kilometer *per one-way commute.* The costs estimated here were doubled to reflect two-way commute (i.e. home to work to home).

Table 10: Calculations of travel time costs for civilians in BRAC-affected PUMAs

Civilians in BRAC-Affected PUMAs	**IV Calculations**
Data from IPUMS	
Average income of all civilian workers in BRAC-affected PUMAs ($2005)	$46,520.68
Average hours worked per week for all civilian workers in BRAC-affected PUMAs (hrs)	39.73
Average weeks worked per year of all civilian workers in BRAC-affected PUMAs (wks)	46.80
Calculations	
Hourly income based on above ($/hr)	$25.02
IV coefficient on worker density (workers/km^2) – low	0.001
IV coefficient on worker density (workers/km^2) – high	0.001
Total daily short-run cost of BRAC for all civilians in BRAC-affected PUMAs ($/day) – low	$13,452,212
Total daily short-run cost of BRAC for all civilians in BRAC-affected PUMAs ($/day) – high	$26,904,424
Total annual short-run cost of BRAC for all civilians in BRAC-affected PUMAs ($) – low	**$3,147,817,634**
Total annual short-run cost of BRAC for all civilians in BRAC-affected PUMAs ($) – high	**$6,295,635,269**

Note: The IV coefficients are measured in terms added log travel time per added workers per square kilometer *per one-way commute.* The costs estimated here were doubled to reflect two-way commute (i.e. home to work to home).

Table 11: Average cost of employment growth for all U.S. workers

All U.S. workers	**IV Calculations**
Data from IPUMS	
Average income of all U.S. workers ($2005)	$44,855.77
Average hours worked per week for all U.S. workers (hrs/wk)	39.94
Average weeks worked per year for all U.S. workers (wks)	46.82
Calculations	
Hourly income based on above ($/hr)	$23.99
IV coefficient on worker density (workers/km^2) – low	0.0007
IV coefficient on worker density (workers/km^2) – high	0.001
Short-run increase in one-way travel time from 10 additional people per km^2 (min/commuter) – low	0.171
Short-run increase in one-way travel time from 10 additional people per km^2 (min/commuter) – high	0.244
Daily short-run cost of 10 additional people per km^2 ($/commuter/day) – low	**$0.07**
Daily short-run cost of 10 additional people per km^2 ($/commuter/day) – high	**$0.20**

Note: The IV coefficients are measured in terms added log travel time per added workers per square kilometer *per one-way commute.* The costs estimated here were doubled to reflect two-way commute (i.e. home to work to home).

APPENDIX A

Table A1: Summary Statistics for DDD Treatment and Control Groups

	Treatment Group		*Control Groups*					
	Military in BRAC-Affected PUMAs		**Civilians in BRAC-Affected PUMAs**		**Military in non-BRAC-Affected PUMAs**		**Civilians in Adjacent PUMAs**	
Variable	**Obs.**	**Mean (std dev)**	**Obs.**	**Mean (std dev)**	**Obs.**	**Mean (std dev)**	**Obs.**	**Mean (std dev)**
One-way commute travel time, 2000-2005 (minutes)	2,790	23 (20)	148,761	24 (22)	7,300	20 (20)	5.5e+07	11 (20)
One-way commute travel time, 2006-2010 (minutes)	7,366	24 (19)	405,412	24 (21)	17,885	21 (19)	1.5e+07	11(19)
Age (yrs)	10,156	32 (8)	554,173	39 (12)	25,185	32 (9)	2.0e+07	37(23)
Family income ($10,000)	10,156	63 (40)	554,173	80 (72)	25,185	63 (42)	2.0e+07	70(73)
Education (yrs)	10,156	8 (2)	554,173	8 (2)	25,185	8 (2)	2.0e+07	6(3)
Female (dummy)	10,156	0.15 (0.36)	554,173	0.46 (0.5)	25,185	0.16 (0.37)	2.0e+07	0.5(0.5)
Vehicles per adult in household (number)	10,156	1.2 (0.71)	554,173	1.2 (0.72)	25,185	1.2 (0.66)	2.0e+07	0.95(0.69)
Family size (number)	10,156	3 (2)	554,173	2.9 (1.6)	25,185	2.79 (1.48)	2.0e+07	3.12(1.75)
Married (dummy)	10,156	0.69 (0.46)	554,173	0.53 (0.49)	25,185	0.68 (0.47)	2.0e+07	0.38(0.48)
Immigrated to U.S. (dummy)	10,156	0.11 (0.31)	554,173	0.18 (0.39)	25,185	0.08 (0.27)	2.0e+07	0.13(0.34)
Hours worked per week	10,156	52 (15)	554,173	40 (11)	25,185	49 (15)	2.0e+07	21(21)
Kids in household (number)	10,156	1.02 (1.17)	554,173	0.83 (1.11)	25,185	0.99 (1.16)	2.0e+07	1 (1)
Bus density (bus workers/km^2)	10,156	0.81 (4.12)	554,169	0.43 (2.49)	25,181	0.34 (1.44)	2.0e+07	5.16(22.8)
Train density (train workers/km^2)	10,156	0.49 (1.56)	554,169	0.25 (0.95)	25,181	0.17 (0.7)	2.0e+07	0.95(3.87)
Lives in urban area (dummy)	10,156	0.21 (0.41)	554,173	0.12 (0.32)	25,185	0.11 (0.32)	2.0e+07	0.15(0.36)
Lives in rural area (dummy)	10,156	0.13 (0.34)	554,173	0.07 (0.26)	25,185	0.13 (0.34)	2.0e+07	0.15(0.36)

Table A2: Summary Statistics for IV Models

	Military in All PUMAs with Military Bases (IV Models)		Civilians in All PUMAs with Military Bases (IV Models)	
Variable	**Obs.**	**Mean (std dev)**	**Obs.**	**Mean (std dev)**
One-way commute travel time, all years (minutes)	716,416	25 (22)	1,100,000	25 (22)
Worker density (workers/km^2)	717,876	3691 (6593)	1,100,000	7304 (16741)
Age (yrs)	717,876	40 (12)	1,100,000	40 (12)
Family income ($10,000)	717,876	83 (75)	1,100,000	83 (75)
Education (yrs)	717,876	7 (2)	1,100,000	7 (2)
Female (dummy)	717,876	0.15 (0.36)	1,100,000	0.51 (0.5)
Vehicles per adult in household (number)	717,876	1 (1)	1,100,000	1 (1)
Family size (number)	717,876	3 (2)	1,100,000	3 (2)
Married (dummy)	717,876	1 (0)	1,100,000	1 (0)
Immigrated to U.S. (dummy)	717,876	0 (0)	1,100,000	0 (0)
Hours worked per week	717,876	40 (11)	1,100,000	40 (11)
Kids in household (number)	717,876	1 (1)	1,100,000	1 (1)
Bus density (bus workers/km^2)	716,416	2 (40)	1,100,000	6 (270)
Train density (train workers/km^2)	716,416	1 (20)	1,100,000	1 (30)
Lives in urban area (dummy)	717,876	0.21 (0.41)	1,100,000	0.16 (0.36)
Lives in rural area (dummy)	717,876	0.13 (0.34)	1,100,000	0.16 (0.37)

APPENDIX B

In addition to our IV regressions of log one-way commute travel time, we also run a set of IV regressions to examine the effect of employment growth on commute departure time and on commute arrival time. The commute departure time in the data set reports the time that the respondent usually left home for work in the previous week, and the commute arrival time reports the time that the respondent usually arrived at work in the previous week. We convert the commute departure time and commute arrival times to minutes from midnight (where, for example, 1 = 12:01am, 60 = 1:00am, 120 = 2:00am, and 1439 = 11:49pm).

Table B1 presents the summary statistics for commute departure time and commute arrival time. For military in BRAC-affected areas, the mean commute departure time is 6:56am and the mean commute arrival time is 7:19am. For all workers in the U.S., the mean commute departure time is 8:09am and the mean commute arrival time is 8:33am.

Tables B2 and B3 present the results of our IV regression of commute departure time from home and commute arrival time to work, respectively, for the civilian-only models. We find some evidence that employment growth may cause civilian commuters to both depart from home later and to arrive at work later, at least for commuters in BRAC-affected PUMAs.

Tables B4 and B5 present the results of our IV regression of commute departure time from home and commute arrival time to work, respectively, for the military-only models. We find evidence that employment growth causes military commuters to both depart from home earlier and to arrive at work earlier.

Table B1: Summary statistics from commute departure time and commute arrival time

Variable	Military in BRAC-affected Areas *Mean (std dev)*	U.S. [1] *Mean (std dev)* [1]
Commute departure time (minutes from midnight)	415.9 (178.0)	488.5 (231.3)
Commute arrival time (minutes from midnight)	438.7 (176.7)	513.0 (231.4)

[1] All employed people between 17-61 years old.

Table B2: **Results of IV models for commute departure time for civilian-only models**

	Dependent variable is commute departure time from home (minutes from midnight)			
	Civilian Models			
	BRAC-affected PUMAs only		All USA	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.645*	0.628	0.031	-0.060
	(0.320)	(0.355)	(0.054)	(0.050)
Control variablesǂ	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	16.32	13.06	159.86	391.43
Observations	120,478	111,796	2,992,612	2,730,860

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

ǂ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table B3: **Results of IV models for commute arrival time for civilian-only models**

	Dependent variable is commute arrival time to work (minutes from midnight)			
	Civilian Models			
	BRAC-affected PUMAs only		All USA	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	0.666*	0.640	0.063	-0.034
	(0.320)	(0.353)	(0.054)	(0.050)
Control variablesǂ	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	16.32	13.06	159.86	391.43
Observations	120,478	111,796	2,992,612	2,730,860

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

ǂ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table B4: **Results of IV models for commute departure time for military-only models**

	Dependent variable is commute departure time from home (minutes from midnight)			
	Military Models			
	BRAC-affected PUMAs only		BRAC-affected PUMAs and adjacent PUMAs	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	-1.565***	-1.759**	-0.621***	-0.444***
	(0.479)	(0.603)	(0.148)	(0.091)
Control variables‡	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	12.08	9.43	25.89	51.16
Observations	6,591	6,286	16,505	15,370

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

‡ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)

Table B5: **Results of IV models for commute arrival time for military-only models**

	Dependent variable is commute arrival time to work (minutes from midnight)			
	Military Models			
	BRAC-affected PUMAs only		BRAC-affected PUMAs and adjacent PUMAs	
	All Commuters	Drivers Only	All Commuters	Drivers Only
Coefficient on worker density (workers/km^2)	-1.553***	-1.735***	-0.600***	-0.423***
	(0.480)	(0.599)	(0.147)	(0.090)
Control variables‡	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Standard errors clustered by household	Yes	Yes	Yes	Yes
First-stage F-statistic	12.08	9.43	25.89	51.16
Observations	6,591	6,286	16,505	15,370

Notes: Standard errors clustered by household are in parentheses. Worker density is instrumented with the change in the number of military individuals in the 2005 BRAC. Significance codes: *** p<0.001, ** p<0.01, * p<0.05.

‡ We use the following control variables:

Individual-level: age, age squared, education, female, married, immigrated to US, hours worked per week, family income, vehicles per adult in household, family size, number of children

PUMA-level: lagged average travel time in PUMA, bus density (bus workers/km^2), train density (train workers/km^2), lives in urban area, lives in rural area, bus density of workplace (bus workers/km^2), train density of workplace (train workers/km^2)