The Local Economic Impacts of Military Personnel Contractions*

Ben Zou†

June 2015

Abstract

Between 1988 and 2000, the number of U.S. military personnel stationed in the United States shrank by 30 percent, and hundreds of local economies with military bases were affected. As military personnel pull out of a locale, demands for local labor, housing, and locally-traded goods decline. In this paper, I jointly estimate the impacts of this personnel reduction on the equilibrium quantities and prices of local labor markets, local housing markets, and local product markets. In order to establish causal identification, I propose and estimate a two-step empirical model combining synthetic control and instrumental variables methods. I find sizable effects of military personnel contractions on civilian employment levels and the numbers of private businesses. But this employment reduction translates into out-migration of local civilian residents to other jurisdictions, resulting in a drop in rental prices that is larger than the drop in wages. I build a simple spatial equilibrium model that describes the equilibrium conditions and derives expressions for welfare calculation. Relating them to my econometric estimates, I show that the welfare cost on workers is small while that on landowners is sizable.

Keywords: Local spillover effects; Local economic dynamics; Military contractions. JEL Code: J21, R12, J61

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*I thank Judith Hellerstein, Sebastian Galiani, and Ethan Kaplan for their continued advice and support. Thanks to John Ham, Ginger Jin, Sergio Urzua, and Ye Zhang, as well as seminar participants at the University of Maryland and the U.S. Department of Labor, and conference participants at the SOLE annual meeting, UEA annual meeting, and the WEAI graduate student workshop for helpful comments. I thank the Employment and Training Administration of the U.S. Department of Labor for providing financial support. The opinions and the remaining errors are mine.

†Michigan State University, benzou@msu.edu.

1 Introduction

Economic activities in a local geographic area interact with each other: shocks to one sector have direct and indirect effects on other agents in the local economy. Economists have long been interested in identifying the size of local economic spillover effects and the mechanisms through which these effects work.[1] The findings of studies on spillover effects have important policy implications as governments at all levels across the world spend billions of dollars on various place-based policies aiming at promoting economic opportunities in certain localities.

In order to fully capture the total impacts on the various stakeholders of the local economy, it is important to simultaneously model and estimate the behavior and interactions of many agents. Most existing studies focusing on local labor market outcomes, usually in terms of the number of jobs created or lost, are likely to miss important parts of the story.[2] Fewer job opportunities depress employment and wages but also make housing and local services more affordable. Restricting attention to the local labor market overlooks this compensating effect. Moreover, the effects of decreased job opportunies on workers' levels of economic activity, may also differ from the effects on welfare: if displaced workers are freely mobile and can easily find jobs elsewhere with competitive wages, their welfare losses are likely to be small. Finally, local shocks also affect the welfare of landowners and the profitability of local firms. The welfare incidence matters for policy. A progressive government, for example, may care more about the welfare of the workers than that of the landowners.

This paper studies the local economic impacts of the contractions of a special industry – the US military – on workers, landowners and firms. I focus on the post-Reagan military personnel cuts between 1988 and 2000, a period during which the size of the US military shrank by 30 percent.[3] The bulk of the cuts took place in locations hosting major military bases. Declining military presence reduces demand for housing and local non-tradable goods, which drives down local housing prices and the price of the non-tradable goods. Some non-tradable sector firms go out of business. Meanwhile, an over-supply of workers relative to job opportunities drives down local wages, and some households choose to leave the local economy in favor of better economic opportunities. The relative strengths and net effects of these intertwined

[1] Adam Smith notes that local economic links help workers and firms to specialize. Marshall (1890) remarks that co-location of related industries promote productivity through economic linkages. Recent studies on local economic spillover effects date back to the economic downturn in the early 1980s when there were large demand shocks to the manufacturing industry in the United States (Topel, 1986; Blanchard & Katz, 1992; Bound & Holzer, 2000).

[2] Many existing studies estimate a local job multiplier, the additional jobs created or lost due to exogenous changes in employment in one sector (e.g., Bartik, 1991; Blanchard & Katz, 1992; Black et al., 2005; Moretti, 2010b).

[3] In a typical year without major wars, the Department of Defense (DoD) spends about 40 percent of its budget on compensation for military personnel, 30 percent on procurement, and the rest on operational costs. During this period, all these components declined substantially. Section 7.2 uses variations in procurement as a robustness check.

channels depend on the parameters of the local economy and are the interests of this empirical study.

There are two challenges to establishing the causal effect: the problems of omitted variables and simultaneity. The omitted variables problem means that there might be location-specific secular trends driven by local fundamentals that may confound with military contractions. For example, if large military bases are frequently located in places with faster economic growth, the effects of military contractions will be under-estimated if the underlying economic trajectories are not taken into consideration. Simultaneity would occur if, in deciding the size of military contraction in each place, the Department of Defense (DoD) avoided large cuts in places with unfavorable transitory shocks in order to minimize negative economic impacts. Failing to correct for this simultaneity problem would also make the OLS estimate biased downward.

I propose a shift-share instrumental variable to address the simultaneity problem. This type of instrument, also known as a Bartik instrument (Bartik, 1991), is widely used in the related literature. The instrumental variable is the interaction between the location's historical military presence and the contemporaneous nationwide contraction in military personnel. The instrument solves the simultaneity problem as long as the national change is not driven by local idiosyncratic shocks and historical military presence is uncorrelated with the transitory shocks. However, this instrument does not solve the omitted variable problem because the historical military presence and the secular trend are both functions of local fundamentals: places with some unobserved advantages are likely to attract large military bases and have better trajectories of economic development. Therefore, the identification of the causal effect using the shift-share instrument hinges on partialling out the secular trend.

I use two different approaches to partial out the secular trend. In the first approach, I include a host of pre-determined county characteristics as covariates. This conventional approach is easy to implement but imposes restrictive parametric assumptions and has the risk of mis-specifying the secular trend. In the second approach, I use a non-parametric method similar to the synthetic control approach used in Abadie et al. (2010). From a large pool of counties without military bases that serve as potential comparisons, I construct for each county with military bases a "synthetic control" that best matches the outcome trajectories in the pre-treatment period. I use the synthetic control's post-treatment trajectories of the outcomes as the counterfactuals for counties with military bases. This approach allows me to account for flexible secular trends without knowing their exact functional forms.

The identification can be thought of as having two steps. The first involves partialling out the secular trends, and the second estimates the partial equation using the Bartik instrument. Potential mis-specification in the parametric approach in the first step may still invalidate the Bartik instrument. I show in a simulation exercise how mis-specified parametric models could lead to substantially biased estimates, while the synthetic control approach obtains estimates close to the true value.

I find sizable effects of military personnel contractions on the levels of local economic activities. I find that, over the 12-year period, cutting one military worker results in the loss of 1.2 civilian jobs and 32,000 dollars in civilian earnings. The effects are concentrated in the non-tradable sectors while the tradable sectors are barely affected, a result often found in the related literature (e.g., Black et al., 2005). I find a large migration response: on average 2.4 civilians leave the local economy for every civilian job loss. High migration response results in small impacts on local wages but big impacts on rental prices. The average size of the impact in the sample is equal to a reduction in the ratio of military personnel to the total local population by one percentage point. This impact reduces local wages by 0.47 percent, or 141 dollars annually, and barely affects the civilian employment to population ratio. In contrast, local rental prices drop by 1.3 percent.

To understand the reduced-form results and calculate welfare impacts on the stakeholders of the local economy, I incorporate a two-sector model in a simple spatial equilibrium framework with workers, landowners, firms, and their interactions. In the model, each location is a small open economy, and capital and labor mobility are costless. Workers have heterogeneous preferences over locations so that some do not move when real wages decline in the local economies where they reside. There are two sectors in the local economy, producing tradable and non-tradable goods, respectively, and workers are interchangeable between the two sectors. The housing market is competitive. The model endogenously determines the local economy's population, employment, wages, housing rental prices, and prices of local non-tradable goods. Military personnel contractions reduce demand for local non-tradable goods and housing. Intuitively, businesses and workers in the non-tradable sectors are directly affected. Displaced workers can work in the tradable sector with lower wages, or migrate out of the local economy for a more competitive wage. For a particular shock, the welfare of workers depends on the flexibility of their location choices and the technology used in the housing, tradable and non-tradable sectors. The welfare of the landowners, on the other hand, depends on changes in rental prices and local population.

To calculate welfare impacts, I first derive expressions for changes in welfare for workers, landowners, and profits for firms as functions of military personnel contractions. I then relate these expressions to the reduced-form estimates. The welfare loss for workers is negligible: as a result of reducing the military personnel to population ratio by one percentage point, workers' utility drops by a mere 0.02 percent. In fact, the utility of the tradable firms increases by 0.3 percent thanks to declining local wages. Landowners bear most of the welfare loss, as rental revenue drops by 3.6%. This result is not surprising since the large migration response suggests that the local labor supply is elastic, but it has different policy implications than more conventional approach to assess welfare which only measures the local economic impact via the change in the number of jobs.

Finally, I investigate how quickly local economies adjust to shocks. Using a year-by-year panel estimation, I find that local economies respond to military personnel contractions quickly. The accumulated effects on employment, earnings, and businesses in the first two years after a particular military cut are close to the magnitude of the accumulated effects over the 12-year period.

This paper has relevant policy implications. The DoD is the largest employer among all federal agencies. After a decade of expansions since 9/11, the US military is again making substantial budget cuts. In general, the non-welfare part of the federal government spending is projected to decline (Congressional Budget Office, 2014). Many local communities that rely heavily on federal spending are concerned that their local economies may be deeply affected. The findings in this paper suggest that workers and local economies exhibited substantial resilience during similar shocks in the 1990s. The size of local economic activity might be smaller as demand shrinks, but a smaller economy does not necessarily mean a worse one. On the other hand, landowners are likely to be most negatively affected, as land cannot move and housing stocks are slow to adjust.[4]

This paper contributes to the literature on local economic dynamics due to exogenous local shocks. Most existing studies estimate a "local job multiplier" based on a partial equilibrium framework. Black et al. (2005) find that losing one job in the coal mining industry causes the loss of 0.35 jobs in the service sector in the same county. Moretti (2010b) finds that an additional job in the tradable sector creates 1.6 jobs in the non-tradable sector in the same metropolitan area. Other papers look at local employment impacts from other sources, such as Chodorow-Reich et al. (2012); Wilson (2012); Serrato & Wingender (2014); Shoag (2012) on the effects of government expenditure, and Autor et al. (2013) on the effects of competition from China. The post-Reagan military personnel contractions were among the largest declines in employment in a single industry in the US history and arguably the largest cuts of government employment. The magnitude of the employment impact found in this paper falls within the range of existing studies.

A partial equilibrium framework may lead to incomplete understanding of local economic impacts. To obtain a fuller picture, one needs to model all the relevant local economic agents and their interactions (Bartik, 1991; Gottlieb & Glaeser, 2008). New developments in spatial equilibrium models extend the Rosen-Roback framework (Rosen, 1979; Roback, 1982, 1988)

[4]There is a recent strand of thought that recommends that depressed local economies "shrink to greatness." For example, one recipe for Detroit is for the city to restore functionality an area suitable for the volume of its current economic activity (Glaeser, 2010).

and allow for welfare analysis on different agents (Moretti, 2010a; Kline & Moretti, 2014). Using this type of models, recent papers show that the welfare implications differ from those based on partial equilibrium frameworks. Taking into consideration house price differences across metroplitan areas, Moretti (2013) shows that the real wage difference between skilled and unskilled workers is smaller than would be indicated by using nominal wages. Glaeser & Gyourko (2005) argue that the durability of housing during local economic downturns provides a natural safety net for residents who choose to stay. Notowidigdo (2013) points out that government benefit programs that kick in during times of local economic distress have a similar role. Diamond (2013), on the other hand, argues that endogenous amenities lead to welfare impacts larger than what nominal wages imply. This paper adopts a similar framework to study the case of military personnel contractions, where reductions in military presence directly hit the non-tradable sector and the housing sector, and the effects spill ovev to other sectors via the shared local labor market and people's migration decisions.

Variation in military spending has been used in the macroeconomics literature for estimating the fiscal multiplier at the national or subnational level (e.g., Nakamura & Steinsson, 2014; Barro & Redlick, 2011; Ramey & Shapiro, 1998). Surprisingly, there are few studies on the impacts of military spending on local economies. Guthrie (1995); Hooker & Knetter (2007); Hultquist & Petras (2012); aus dem Moore & Spitz-Oener (2012) are among the few that study local impacts of military personnel contractions. These papers focus on local labor market outcomes and, in general, do not address potential endogeneity concerns.

The rest of the paper proceeds as follows: Section 2 introduces the setting and historical background. Section 3 presents the model. Section 4 describes the empirical approach. Section 5 describes the data and the sample. Section 6 presents the empirical results, relates the model and the empirical results, and calculates welfare impacts. Section 7 investigates how fast local economies adjust to new equilibria. Section 8 summarizes the findings.

2 Background

2.1 Military Personnel and Local Economies

The vast majority of military personnel live in or around military bases. In 1987, 353 major military bases in the US were located in 381 counties. The personnel located in these counties accounted for over 90 percent of total US military personnel. These counties are spread across the United States, from large coastal metropolises to sparsely populated deserts. This geographic dispersion is partly due to national defense considerations: the military should be somewhat evenly distributed across the territory such that it can quickly react to threats to national security. Economic and other practical considerations also affect location choices for military bases. For example, Naval bases must be close to large bodies of water, while testing and training areas, due to their demand for large pieces of land, are often located in places with low population density and low land values.

On average, counties with military bases (henceforth called "base counties") are larger and more densely populated than counties without military bases ("non-base counties"). In 1980, base counties accounted for about 12 percent of the total county-level jurisdictions in the United States, but contained about 50 percent of the country's population. Their economic performance was also better: private sector employment in base counties grew by 22 percent between 1980 and 1987, almost twice as much as it did in non-base counties. However, the differences in averages mask important heterogeneity within each group. As the military bases are located across the country, the local economies where they are located have many different types of geographic and economic characteristics. It is therefore a potential econometric concern that cuts in military personnel may be correlated with the underlying characteristics of the local economy.

The presence of military bases generates three types of direct impact on the local economy. First, local military bases employ civilian workers, many of whom work on the bases. In 1990, the DoD employed 1 million civilian workers, making it the largest employer of civilian workers among federal government agencies.[5] Second, the military bases create demand for goods and services from local contractors. Third, military personnel create demand for housing and local non-tradable goods. Military contractions directly reduce the demand for local labor, non-tradable goods, and housing, which in turn affects other parts of the local economy.[6]

2.2 Post-Reagan Military Contractions

The size of the military as measured by the number of men and women in uniform in the United States has been declining since the end of WWII. This trend paused in the 1980s when the Reagan Administration significantly expanded military spending while the number of military personnel stayed stable.[7] Political gridlock in deciding which military bases to cut contributed to the pause, as members of Congress and local politicians viewed letting military bases be slashed in their jurisdictions under their watch as political suicide.

By the end of the Reagan Administration, it became clear that military contractions were

[5]The 2012 Statistical Abstract. Table 499. url: http://www.census.gov/compendia/statab/2012/tables/12s0499.pdf. Last accessed in Oct, 2014.

[6]I ignore the effects on local labor supply of new veterans. I find that military personnel contractions in the sample period do not increase the number of veterans in the county.

[7]The expansion was mainly concentrated in military procurement for developing new weapons, but the number of military personnel also stopped declining during this period.

necessary. The international geopolitical situation changed dramatically in the late 1980s as the winding down of the Cold War prompted a reduction in military capacity in the United States. Domestically, the federal fiscal situation after large tax cuts and spending hikes throughout the Reagan Administration also made military cuts necessary. To circumvent political gridlock, in 1988, the Base Re-Alignment and Closure (BRAC) Act was passed. An independent commission with members jointly nominated by the president and Congress became responsible for selecting military installations to be re-aligned or permanently closed, based on a list of the DoD's recommendations. The BRAC insulated individual members of Congress from the political penalties of potential shutdowns of military bases in their jurisdictions. Military values and cost-saving were the main criteria for choosing military bases to be re-aligned or closed, although potential economic impacts were also an explicit consideration.[8]

The top graph in figure 1 shows the trajectory of the number of active duty military personnel between 1975 and 2010. Over two-thirds of the 535 major military bases were affected by the four rounds of BRAC in 1988, 1991, 1993, and 1995. Many bases that were not chosen for closure by the BRAC also experienced substantial declines in personnel as parts of their operations were cut or moved. The declining trend did not stop until the 9/11 terrorist attacks in 2001.[9] Between 1988 and 2000, the number of military personnel dropped by over 30 percent, discharging about half a million military personnel. It was one of the largest negative shocks generated by a single industry in the past 50 years of US history.[10] I refer to this episode of military personnel contractions as "post-Reagan military contractions".

The post-Reagan military contractions affected counties with military bases since most military personnel were stationed in these counties. As the bottom graph of figure 1 shows, between 1990 and 2000, the number of military personnel in base counties dropped from 1.47 million to 1.05 million, a 28.5 percent decline. In these counties, the military personnel to population ratio dropped from 2.61 percent in 1988 to 1.68 percent in 2000. In contrast, the non-base counties saw negligible military personnel contractions, as military personnel dropped slightly from 0.11 percent of the population in 1988 to 0.08 percent of the population in 2000. To estimate the effects of military personnel contractions on local economies, I focus on base counties. The non-base counties, with negligible military presence, serve as potential comparisons.

Although not a priority, the potential impact on local economies was an explicit consideration for the DoD and the BRAC Commission in deciding where to cut military personnel

[8]The military value under consideration includes the current and future mission capabilities, operational readiness; the availabiity and condition of land, facilities, and associated airspace; the ability to accommodate contigency, mobilization, surge, etc.

[9]Although there was another round of BRAC in 2005, the size of active duty military personnel has been fairly stable at around 1 million since 2000.

[10]A comparable figure is that between 1977 and 1987, the United States shed about 500,000 jobs in the auto industry and 350,000 jobs in the steel industry (Feyrer et al., 2007).

and by how much. During the process of deciding which bases would be closed or realigned, objections from local communities citing economic concerns were numerous, and there were indeed cases in which the BRAC Commission rejected large cuts proposed by the DoD due to local economic concerns.[11] In addition, considerations not directly related to local labor market conditions, such as cost-saving considerations and military values, can be confounded with economic outcomes. For example, since good labor market conditions drive up local prices, if other factors remain constant, shrinking the military presence in these areas would lead to sizable savings for the DoD. These explicit and implicit considerations for local economic conditions raise concerns about the endogeneity of military personnel contractions.

3 A Spatial Equilibrium Model

3.1 Overview

In order to describe the effects of military personnel contractions on local economies, this section presents a spatial equilibrium model of local economies. The model serves three purposes. First, it describes the mechanisms through which military personnel contractions affect various stakeholders in the local economy. Second, its equilibrium conditions suggest a vector of outcomes of interest, which I will estimate empirically in sections 4 through 6. Third, it allows me to derive expressions for welfare changes of the stakeholders in the local economy, which I bring to the data in section 6.4.

This model adapts from the framework for local labor market equilibrium in Kline & Moretti (2014). The model features many locations. Each location is a small open economy in which households, landowners, and firms interact with each other.[12] Capital is elastically supplied nationwide. The key feature of this framework is that the households, besides deriving utility from consumption, have heterogeneous preferences over locations. Shocks to the local economy will be inframarginal for some households with strong preferences for the locality in making migration decisions. These households will therefore bear the full welfare consequences of changes in local wage, price, and rent. This feature distinguishes this kind of model from the standard Rosen-Roback framework (Rosen, 1979; Roback, 1982, 1988) where workers are perfectly mobile, and migration fully arbitrages differences in local real wages across locations.

Military personnel contractions directly reduce the demand for locally-traded goods, but

[11] For example, the proposed closure of the submarine base in New London, CT, was rejected by the 2005 BRAC Commission partly because "[...] the Commission found the argument of overall economic impact compelling". (2005 BRAC Commission Report to the President)

[12] Landowners are assumed to be absent. Throughout the paper, the term "household" is interchangeable with the term "worker".

nationally-traded goods are not directly affected. In order to model this, I extend this framework by introducing a simple two-sector model. Firms in the non-tradable sector, facing a competitive market, produce goods and services that are traded within the local economy. The equilibrium of non-tradable goods is obtained within the local economy with the local price endogeneously determined. Each firm in the tradable sector produces a differentiated good that is sold in the national market. Firms in the tradable sector are indirectly affected by the military personnel contractions through changes in the conditions of the local labor market they share with firms in the non-tradable sector. Introducing a two-sector model in the spatial equilibrium framework thus adds an inter-sectoral wedge in local labor supply besides the wedge generated by migration.[13]

3.2 Household Problem

Each household i chooses where to live and how much to consume. Households consume tradable and non-tradable goods and housing. Households all have the same productivity and each provides one unit of labor inelastically.[14] For a household that lives in location c, its utility maximizing problem can be written as

$$\max_{h_{ic}, X_{ic}^N, X_{ic}^T} u_{ic} = \ln A_c + \alpha \ln h_{ic} + \beta \ln X_{ic}^N + (1-\alpha-\beta)\ln X_{ic}^T + e_{ic},$$

$$\text{s.t., } r_c h_{ic} + p_c X_{ic}^N + p_T X_i^T = w_c$$

where A_c is the dollar value of amenities in location c, which are freely available to all its residents. h_{ic}, X_{ic}^N, and X_{ic}^T are, respectively, the amount of housing, the amount of non-tradable goods, and the amount of the tradable goods consumed by household i. The tradable good, X^T, is a composite good with many varieties of tradable goods

$$X^T = (\int_{j\in J} x_j^{(\sigma^T-1)/\sigma^T} dj)^{\sigma^T/(\sigma^T-1)},$$

[13]Kovak (2013) includes a local non-tradable sector in the analysis of trade shocks on local economies. But his model does not allow heterogeneity in preference for locations. Yoon (2014) builds a two-sector model with idiosyncratic individual preference over locations in a dynamic model of location choices. Unlike the model introduced in this paper, the changes in sectoral composition are driven by nationwide factor-biased technological change in the two sectors.

[14]Appendix B.1 provides a simple extension of the household problem that allows for unemployment. In that extension, each household independently draws an idiosyncratic utility from leisure (or distaste for work). The labor force participation decision is binary and is made by comparing utility from working and that from not working. The local unemployment rate is thus determined by the marginal worker who is indifferent between working and not. Given the same distribution of idiosyncratic preference for leisure, the local unemployment rate is in turn determined by the local real wage level. Local unemployment rates differ only because local real wage rates differ. In the empirical section, I find that there is no effect on local unemployment rates, which suggests that inelastic supply of labor is not a restrictive assumption here.

where $j \in J$ is one variety of the partially substitutable tradable goods, $\sigma^T > 1$ is the elasticity of substitution between any two varieties.[15] p_T is the price of the composite tradable good, which is standardized to 1. Both rental price, r_c, and non-tradable goods price, p_c, are determined by local housing and non-tradable goods markets equilibria and differ across locations. The utility is in the Cobb-Douglas form. α, β, and $1 - \alpha - \beta$ represent the shares of income spent on housing, non-tradable goods, and tradable goods, respectively.

e_{ic} is the idiosyncratic utility household i derives from living in location c. e_{ic} is assumed to be *i.i.d* and follows a type I extreme value distribution with dispersion σ^W.[16] Solving the household's problem, household i's indirect utility from living in location c is

$$v_{ic} = u_c + e_{ic} \tag{1}$$

u_c, which is equal to $a_0 + \ln w_c - \alpha \ln r_c - \beta \ln p_c + \ln A_c$ is the deterministic term common to each household that lives in location c, where a_0 is a constant. u_c can be also thought of as a measure of real wages adjusted for local living expenses and amenities.

Each household chooses a location to live in such that v_{ic} is maximized. The population size (and labor supply) in location c can be expressed as[17]

$$\ln N_c = \frac{1}{\sigma^W}(a_0 + \ln w_c - \alpha \ln r_c - \beta \ln p_c + \ln A_c) + \frac{1}{\sigma^W} a_C. \tag{2}$$

Denote c' as a location other than location c. $a_C = \ln \sum_{c'} \exp(u_{c'}/\sigma^W)$, which is a constant. Local population is determined by the local real wage and the distribution of preference across locations. The inverse of the dispersion of idiosyncratic preference across locations, $1/\sigma^W$ is the elasticity of local labor supply with respect to local real wages u_c. Intuitively, if σ^W is large, households have strong preferences over different locations, and local labor supply is inelastic. After a negative shock, as many households do not migrate out of the local economy, real wages drop and the remianing households bear a large share of the welfare loss. In equilibrium, local real wages can vary substantially across locations. Alternatively, if σ^W is small, households do not have strong preferences across locations, and local labor supply is elastic. After a negative shock, local real wages do not change by much in the new equilibrium and neither does the welfare of the remaining households.

[15] This constant elasticity of substitution (CES) demand function is widely used in the labor and trade literature. $\sigma^T > 1$ indicates that x_j and $x_{j'}$ are substitutes. See Suarez-Serrato & Zidar (2014) for a recent application in the spatial general equlibrium framework.

[16] The CDF is $F(e_{ic}) = exp(-exp(-(e_{ic})/\sigma^W))$

[17] See Appendix B.2 for derivation.

3.3 Housing Market

The Cobb-Douglas utility function predicts that each household spends a constant share α of its income on housing; local residents' total spending on housing is $N_c \alpha w_c$. Denote $m_c^H > 1$ as the demand shift due to the military presence.[18] The aggregate housing demand in location c is

$$H_c^D = N_c \alpha w_c m_c^H / r_c. \tag{3}$$

The housing sector in location c has productivity κ_c. Housing supply in location c responds positively to local rental price but is restricted by geographic characteristics, land use regulations, and other costs, which are governed by location-specific elasticity η_c,

$$H_c^S = \kappa_c r_c^{\eta_c}. \tag{4}$$

The local housing market equilibrium is obtained by combining equation 3 and equation 4 and can be expressed in log forms

$$(1 + \eta_c)\ln r_c = \ln N_c + \ln w_c + \ln m_c^H + a_H, \tag{5}$$

where $a_H = \ln\alpha - \ln\kappa_c$. Equation 5 is intuitive: the local rental price is higher when the local population (N_c) is larger, local wage (w_c) is higher, households spend a larger share of income on housing (α), and when housing is hard to produce either because of natural or policy restrictions (low η_c) or low productivity (low κ_c).

3.4 Local Businesses

3.4.1 Firms in the Tradable Sector

Each firm in the tradable sector produces one variety of good $j \in J$. Since all j's are symmetric, without loss of generality, I assume that there is only one firm producing durable goods in location c and it produces one particular variety j. The production function is in the Cobb-Douglas form with constant returns to scale and labor's share equal to h_T

$$x_j = B_{Tc} (N_c^T)^{h_T} (K_c^T)^{1-h_T}, \tag{6}$$

where B_{Tc} is the total factor productivity.

[18] m_c^H is modeled as multiplicative to the demand generated by local residents for tractability of the model. To be consistent with the model, in the empirical part, military presence is specified as the number of military personnel as a ratio of population.

In a world of differentiated goods, each firm is a monopolistic competitor in the national market. It faces a downward sloping demand curve and earns a positive profit. The demand for good j can be written as

$$x_j = \frac{I_j}{p_j^{\sigma^T}}, \tag{7}$$

where I_j is the nation's total spending on x_j, which is a constant; $\sigma^T > 1$ is the elasticity of substitution between any two varieties, and p_j is the national price for j. Since j is only one of many varieties in the tradable goods market, changes in the production of x_j do not affect the price of the composite tradable good, which is still at price $p_T = 1$. The firm is a price-taker in factor markets; it solves the following profit-maximizing problem

$$\max_{N_c^T, K_c^T} \pi_j = p_j x_j - w_c N_c^T - \rho K_c^T. \tag{8}$$

Solving this problem, labor demand in the tradable sector is[19]

$$\ln N_c^T = [(1 - h_T)(\sigma^T - 1) - \sigma^T] \ln w_c + a_{TL}. \tag{9}$$

As a standard result of the CES production function, the log profit can be expressed as

$$\ln \pi_j = \ln \varphi_j + (\sigma^T - 1)[\ln B_{Tc} - h_T \ln w_c - (1 - h_T) \ln \rho], \tag{10}$$

where φ_j is a constant.

3.4.2 Firms in the Non-tradable Sector

Firms producing non-tradable goods face a competitive market.[20] Each firm's production

[19] a_{TL} is a constant. Appendix B.3 provides detailed derivations for the problem of the firms in the tradable sector.

[20] The assumption that the firms producing tradable goods are monopolistic competitors while the firms producing non-tradable goods are perfectly competitive rests on both economic and technical explanations. Economically, the differentiable goods in the tradable sector are a result of the consumer's "love for variety." On the other hand, firms in the non-tradable sector are often small-scale service establishments that provide homogeneous services and fit the environment of perfect competition. Technically, in order to close the model, I need to specify these market structures for both sectors. If the firm in the tradable sector earns zero profit, its labor demand is flexibly adjusted such that the total local labor supply will not change after the shock. This is because local labor is supplied relatively more inelastically than capital. A firm in a perfectly competitive market facing exogenously given prices accommodates changes in labor supply by freely adjusting its capital input. In order to generate labor mobility across regions, I need to introduce a wedge such that the firm in the tradable sector faces other restrictions in adjusting its production.

function is also in the Cobb-Douglas form with constant returns to scale

$$X_c^N = B_{Nc}(N_c^N)^{h_N}(K_c^N)^{1-h_N}, \tag{11}$$

where B_{Nc} is the total factor productivity of the local non-tradable sector. The firm is a price-taker, while the output price is determined by the equilibrium of local non-tradable goods. The firm maximizes its profit by solving the following problem

$$\max_{N_c^N, K_c^N} \pi_c^N = p_c B_{Nc}(N_c^N)^{h_N}(K_c^N)^{1-h_N} - w_c N_c^N - \rho K_c^N. \tag{12}$$

Solving this problem, the demand for labor in the non-tradable sector can be written as[21]

$$\ln X_c^N = \ln N_c^N + (1-h_N)\ln w_c - (1-h_N)\ln\rho + a_{NX}. \tag{13}$$

Local demand for non-tradable goods can be expressed as

$$X_c^N = \frac{\beta w_c N_c m_c^N}{p_c}, \tag{14}$$

where β is the share of income spent on non-tradable goods. $\beta w_c / p_c$ is the amount of non-tradable goods demanded by each civilian household. $m_c^H > 1$ is the demand shifter for the non-tradable goods, generated by the military presence in the local economy.

The equilibrium of the non-tradable goods is achieved within the local economy

$$\ln N_c^N - \ln N_c = h_N \ln w_c + \ln m_c^H - \ln p_c + a_{NL}. \tag{15}$$

Finally, the zero profit condition in the non-tradable sector yields

$$h_N \ln w_c = \ln p_c + b_N. \tag{16}$$

3.5 Equilibrium Conditions

The equilibrium of the local economy can be described in 5 equations: (1) local labor supply in equation 2, (2) local housing market equilibrium in equation 5, (3) labor demand in the tradable sector in equation 9, (4) labor demand in the non-tradable sector in equation 15, (5) zero profit condition for firms in the non-tradable sector in equation 16. We are interested in the effects of changes in military presence, Δm_c^H, Δm_c^N, on other outcome variables, differentiating these

[21] Detailed steps for the solution of this problem, as well as other conditions for the non-tradable sector listed below, are included in Appendix B.4.

equlibrium conditions yields

$$\sigma^W \Delta \ln N_c = \Delta \ln w_c - \alpha \Delta \ln r_c - \beta \Delta \ln p_c \tag{17}$$

$$(1+\eta_c)\Delta \ln r_c = \Delta \ln N_c + \Delta \ln w_c + \Delta \ln m_c^H \tag{18}$$

$$\Delta \ln N_c^T = [(1-h_T)(\sigma^T - 1) - \sigma^T]\Delta \ln w_c \tag{19}$$

$$\Delta \ln N_c^N - \Delta \ln N_c = h_N \Delta \ln w_c + \Delta \ln m_c^N - \Delta \ln p_c \tag{20}$$

$$h_N \Delta \ln w_c = \Delta \ln p_c. \tag{21}$$

3.6 Welfare Impacts

In this subsection I derive expressions for the impacts of military personnel contractions on the welfare of workers, landowners, and firms in the tradable sector.[22]

3.6.1 Workers/Households

Figure 2 illustrates the impacts on workers as the local real wage (u_c) drops. The horizontal axis represents the whole population of the nation, aligned by increasing e_{ic}, household i's preference for location c, from left to right. The vertical axis shows the utility of household i living in location c or somewhere else c'.

The solid upward sloping line shows that the utility of living in location c increases with e_{ic}. The downward sloping line in dash-dots shows that the utility of living somewhere else drops as e_{ic} increases. The intersection of the two lines determines the marginal household, with $e_{ic} = e_{ic}^*$, which is indifferent between either location. Every household that has $e_{ic} > e_{ic}^*$ chooses to live in location c. Location c has a population equal to $1 - F(e_{ic}^*) = N_c$, where $F(\cdot)$ is the cumulative distribution function for e_{ic}.

Now consider a decline in u_c to u_c' due to military personnel contractions. The new utility of living in c as a function of e_{ic} moves down to the dashed line. Some households originally living in location c that have e_{ic} just above e_{ic}^* will migrate out. The new marginal household, with the idiosyncratic preference for location e_{ic}^{**}, will be determined by the intersection of the dash-dotted line and the dashed line. Population in location c drops to $1 - F(e_{ic}^{**}) = N_c'$.

[22] Firms in the non-tradable earn zero profit, so they do not bear welfare incidence.

Households that migrate and those that stay bear different welfare incidences. Households that choose to migrate out of location c have idiosyncratic preferences such that $e_{ic} \in (e_{ic}^{*}, e_{ic}^{**})$. These households suffer from a loss in utility, as they have to move to a less desirable location. For the household with $e_{ic} = e_{ic}^{*}$, welfare loss is zero; for the household with $e_{ic} = e_{ic}^{**}$, the loss is equal to $\Delta u_c = u_c - u'_c$; for households with $e_{ic}^{*} < e_{ic} < e_{ic}^{**}$, the welfare loss is somewhere in between. $\Delta\ln N_c$ share of location c's original residents choose to leave. The total loss for movers is illustrated in the graph as area B, which can be approximated by $\Delta\ln N_c \cdot \Delta u_c/2$. Households that have idiosyncratic preferences for location c such that $e_{ic} > e_{ic}^{**}$ choose to stay. Each of these households bears a drop in utility that is equal to Δu_c. $(1 - \Delta\ln N_c)$ share of residents choose to stay. The total welfare loss for remaining households is illustrated in the graph as area A and can be expressed as $(1 - \Delta\ln N_c) \cdot \Delta u_c$. The total welfare change for households can be approximated as

$$\Delta V^W = (1 - \Delta\ln N_c) \cdot \Delta u_c + \frac{1}{2}\Delta\ln N_c \cdot \Delta u_c.$$

Recall that $\Delta u_c = \Delta\ln w_c - \alpha\Delta\ln r_c - \beta\Delta\ln p_c$, and plug in equation 21 for $\Delta\ln p_c$. We have the welfare change for workers

$$\Delta V^W = (1 - \frac{1}{2}\Delta\ln N_c) \cdot [(1 - \beta h_N)\Delta\ln w_c - \alpha\Delta\ln r_c] \tag{22}$$

3.6.2 Landowners

The welfare change for landowners is equal to the change in aggregate rents

$$\Delta V^H = \Delta\ln(r_c H_c) = \Delta\ln r_c + \Delta\ln H_c, \tag{23}$$

where H_c is the number of equilibrium housing units.

3.6.3 Firms in the Tradable Sector

The welfare change for the firm in the tradable sector is the change of its profit (equation 10)

$$\Delta V^T = \Delta\ln\pi_j = -(\sigma^T - 1)h_T\Delta\ln w_c. \tag{24}$$

Notice that $-(\sigma^T - 1)h_T < 0$, the firm in the tradable sector *gains* from a negative demand shock to the non-tradable sector, since local labor becomes cheaper.

3.7 Implication for Empirical Study

The model provides guidance for empirical studies. The equilibrium conditions and welfare implications suggest a vector of outcomes of interest $\{\Delta \ln p_c, \Delta \ln w_c, \Delta \ln r_c, \Delta \ln H_c, \Delta \ln N_c, \Delta \ln N_c^N, \Delta \ln N_c^T, \Delta H_c\}$.[23] We investigate all these outcomes in the empirical section. The model also involves a vector of parameters $\{\alpha, \beta, h_T, h_N, \sigma^T, \sigma^W, \eta_c\}$. I borrow from the macro-level data and existing studies to determine the values of these parameters whenever they are used.

4 Econometric Approach

4.1 Estimation Model

The impacts of the post-Reagan military personnel contractions on local economic outcomes over the period of 1988 and 2000 can be estimated as

$$\Delta y_{kc} \quad = \quad \beta_k \Delta mil_c + \Delta \xi_{kc}. \tag{25}$$

$\Delta mil_c = mil_{c,2000} - mil_{c,1988}$ is the change in military presence in county c, where $mil_{c,t} = Mil_{ct}/Pop_{c,1980}$ is the number of military personnel in county c in year t scaled by its population in 1980, such that the impact is always proportional to the size of the local economy. Since population is also an outcome variable of interest, I use population data from 8 years prior to the cuts to avoid possible endogeneity. 1980 is also a census year, so the population count is more accurate and the division error is reduced. $\Delta y_{kc} = y_{kc,2000} - y_{kc,1988}$ is the change in outcome k of county c.[24] y_k may represent each of the following: (1) civilian employment divided by 1980 population, $emp_c = Emp_c/Pop_{c,1980}$; (2) earnings divided by 1980 population, $inc_c = Inc_c/Pop_{c,1980}$; (3) civilian population divided by 1980 population, $pop_c = CivPop_c/Pop_{c,1980}$; (4) log median rental price, $\ln r_c$; (5) private sector business establishments divided by 1980 population, $est_c = Est_c/Pop_{c,1980}$; (6) log average county wage, $\ln w_c$; (7) occupied housing units divided by 1980 population, $h_c = H_c/Pop_{c,1980}$; (8) civilian employment by sector s divided by 1980 population, $emp_{sc} = Emp_{sc}/Pop_{c,1980}$. These are the outcomes of interest as suggested by the model in section 3.

$\Delta \xi_{kc}$ is the composite error term that includes everything other than military personnel contractions that affects the dependent variable. I separate it into two components,

$$\Delta \xi_{kc} = \Delta \gamma_k \lambda_c + \Delta \varepsilon_{kc}.$$

[23] We do not observe price for local non-tradable good p_c, but it can be handily expressed by a function using equation 21.

[24] Some outcomes are are measured between 1990 and 2000.

The first term captures the secular trend of outcome k determined by time-invariant county characteristics λ_c. The term $\Delta\gamma_k\lambda_c$ exists in this long-differenced specification when there are location-specific trends in the outcome variables. For example, a county with a seaport is likely to be on a different labor market trajectory from a county in the desert. $\Delta\varepsilon_{kc}$ captures other unobservable contemporaneous shocks pertinent to the outcome. An example for $\Delta\varepsilon_{kc}$ is a weather shock in the period when the long difference is taken. I assume that $\Delta\gamma_k\lambda_c$ and $\Delta\varepsilon_{kc}$ are orthogonal to each other.

Both λ_c and $\Delta\varepsilon_{kc}$ are potentially unobservable. The OLS estimation of equation 25 can be biased since both $\Delta\gamma_k\lambda_c$ and $\Delta\varepsilon_{kc}$ can be endogenous, though for different reasons. The first is a omitted variable problem. Location choices for military bases are not random; particular locational characteristics both attract military bases and affect trends in economic performance. Larger cuts in military personnel are also concentrated in places with large military bases, if these places are growing at a different rate, $\Delta\gamma_k\lambda_c$ and Δmil_c can be correlated. The second is a simultaneity problem. The DoD may avoid large cuts in places experiencing unfavorable idiosyncratic shocks in order to minimize the economic and political cost of military contractions, so $\Delta\varepsilon_{kc}$ and Δmil_c can be correlated.

When locational characteristics have no effect on the outcome variable or the effects are time-invariant such that long-differencing cancels out the effects, $\Delta\gamma_k\lambda_c = 0$. In this case, we can use a simple instrument to address the simultaneity problem. The instrumental variable I propose is the shift-share predictor widely used in the literature.[25] Specifically, I instrument the actual cut in military personnel in each location with the product of its pre-determined military presence and the size of the nation-wide cut. That is

$$\Delta mil_c^{IV} = mil_{c,1987} \cdot \frac{NtlMil_{2000} - NtlMil_{1988}}{NtlMil_{1988}}, \tag{26}$$

where $mil_{c,1987} = Mil_{c,1987}/Pop_{c,1980}$ is the military personnel to population ratio in county c the year before the post-Reagan military contractions. $NtlMil_t$ is the total number of military personnel nationwide in year t. $(NtlMil_{2000} - NtlMil_{1988})/NtlMil_{1988}$ is the percent change in nationwide military personnel between 1988 and 2000. Therefore, the instrumental variable is the predicted size of military personnel contractions in county c had the DoD adopted a simple rule of cutting military personnel everywhere by the same proportion. The instrument is valid as long as neither the pre-determined military presence nor the national trend is correlated with the idiosyncratic shock $\Delta\varepsilon_{kc}$. The nationwide military cuts were unlikely to be driven by local economic shocks in some particular locations. The post-Reagan military contractions were motivated by national political and fiscal situations and each location is small compared with

[25] Also known as the Bartik instrument due to Bartik 1991.

the whole nation.[26]

The instrument is invalid when $\Delta\gamma_k\lambda_c \neq 0$ because Δmil_c^{IV} can be correlated with $\Delta\gamma_k\lambda_c$. To see this more clearly, notice that since the second term of Δmil_i^{IV} is the same for all observations in the long-difference equation, the variation in the instrument only comes from $mil_{c,1987}$ (denote as $\Delta mil_c^{IV'}$), which might be correlated with λ_c. For example, the fact that Washington, DC is the capital city (λ_c), leads to both large presence of military personnel ($mil_{c,1987}$) and the fact that it attracts private sector economic activities seeking political connection, and thus the city has promising trends in economic performance ($\Delta\gamma_k\lambda_c$). Therefore, the instrument is only valid conditional on the county-specific secular trend $\Delta\gamma_k\lambda_c$.[27]

I use two approaches to partial out the county-specific secular trends. First, in a standard approach, I include observable pre-determined county characteristics in equation 25 in place of $\Delta\gamma_k\lambda_c$. That is, I estimate the following equation by the Two-Stage Least Squares estimator using $\Delta mil_c^{IV'}$ as the instrument for Δmil_c

$$\Delta y_{kc} = \beta_k \Delta mil_c + \mathbf{X}_{kc} \cdot \gamma_k + \varepsilon_{kc}. \tag{27}$$

Each observation in the regression is a county with military bases in 1987. $\mathbf{X}_{kc}$ is a vector of pre-determined county characteristics.[28] The identifying assumption is that the choice of the pre-determined characteristics correctly specifies the secular trends. This approach has a few limitations. First, it imposes parametric assumptions: it assumes that secular trends in all counties can be described by the same data-generating process. Since military bases are spread across the United States in all kinds of economic and geographic situations, a single data-generating process may fail to work for every county. More importantly, the paucity of information on county characteristics which I collect from population censuses and County Business Patterns may fail to correctly specify the secular trends, which may lead to inconsistent estimates.

[26] I test for this possibility in the Appendix by excluding local economies that were most likely to have influenced national policy. Results are robust.

[27] In general, the Bartik instrument based on pre-determined sectoral composition can be correlated with time-invariant local fundamentals. As long as the effects of the fundamentals are not constant, differencing or controlling for location dummies cannot get rid of their effects, making the Bartik instrument invalid and the two-stage least squares estimate inconsistent. This point is worth stressing since many papers that use the Bartik instrument do not make this assumption explicit.

[28] These variables are constructed from various data sources including population censuses, Regional Economic Accounts from the Bureau of Economic Analysis, County Business Patterns, and County Data Books. **X** includes state dummies and metropolitan status; civilian employment, earnings level (scaled by 1980 population) and growth from 1980 to 1987; log median housing price in 1980, 1990, and their difference; number of private business establishments (scaled by 1980 population) and growth from 1980 and 1987; demographic (racial, educational, age) and industrial (2-digit sectors) composition in the latest available year; and other social and economic indicators such as crime rate, number of physicians per 10,000 people, population density, road density, area, and terrain. When appropriate, **X** also includes the quadratic forms of all aforementioned variables. I also use a Bayesian Model Averaging (BMA) approach to select the most relevant covariates (Hoeting et al., 1999). The results from using **X** and those from the BMA are very similar.

4.2 A Generalized Synthetic Control Approach

In this subsection, I propose an alternative approach in order to partial out secular trends. This non-parametric approach eliminates $\Delta\gamma_k\lambda_c$ by constructing a counterfactual based on a large number of counties that did not have military bases in 1987. The idea is simple: since there was little change in the size of the military presence between 1980 and 1987 (see figure 1), the changes in outcome variables were on average driven by the secular trends. If I can find for each base county a comparison county with the same trajectories of the outcome variables in the period prior to the treatment, I can use the comparison county's outcomes in the period of treatment to represent the secular trends of the county with military bases.

The comparison is constructed as the weighted average of non-base counties. Formally, denote $c \in I$ as a base county, and $j \in J$ as a non-base county. For each county c, there is a set of weights, $w_{cj} \in \mathbf{W}_{cj}$, such that

$$\Delta\gamma_{kc}\lambda_c = \sum_{j\in J} w_{cj}\Delta\gamma_{kj}\lambda_j. \tag{28}$$

Note that there is no k subscript for the weights as the same set of weights should match the secular trend of any outcome variable k. This means that the constructed comparison county is the same in the pre-treatment period in all dimensions of interest. The weights are well behaved in the sense that they are bounded between 0 and 1 ($w_{cj} \in [0,1]$, $\forall c, j$) and sum up to 1 ($\sum_j w_{cj} = 1$).

Equation 28 is the identification assumption, as we do not observe λ_c. In practice, I calculate weights for each base county c such that the following distance is minimized

$$w_{cj} = \underset{w_{cj}}{argmin} ||\mathbf{Z}_c - \sum_{j\in J} w_{cj}\mathbf{Z}_j||. \tag{29}$$

$\mathbf{Z}$ is a vector of variables for which the distance is minimized. $\mathbf{Z}$ includes the pre-treatment trajectories of the local economic conditions.[29]

The underlying identification assumption is that by matching on the pre-treatment trajectories of the outcome variables, we are capturing the underlying mechanisms of the secular trends. This approach makes no assumption about the underlying determinants of the secular trends, and it allows for arbitrary functional forms of secular trends for each base county.

[29] I pick the important outcome variables as predicted by the model. Specifically, these variables are $(Emp_{c,1984} - Emp_{c,1980})/Pop_{c,1980}$, $(Emp_{c,1987} - Emp_{c,1980})/Pop_{c,1980}$, $(Inc_{c,1984} - Inc_{c,1980})/Pop_{c,1980}$, $(Inc_{c,1987} - Inc_{c,1980})/Pop_{c,1980}$, $r_{c,1990} - r_{c,1980}$, $p^h_{c,1990} - p^h_{c,1980}$. In fact, the results are robust to alternative set of predictors. All the predictors are given the same weight in the loss function. The results are quantitatively similar when the inverse of standard deviation is used as weights. As in all matching-based methods, there is a tradeoff between the number of variables to be matched on and the average matching quality for each variable.

This approach is similar in spirit to the synthetic control method (Abadie et al., 2010). In the standard synthetic control approach, a counterfactual, called the synthetic control, is constructed based on the past trajectory of the outcome variable up to the period of treatment. The treatment effect is obtained by subtracting the outcome of the synthetic control from the real outcome. I extend this approach in three important dimensions. First, instead of focusing on one outcome variable, I match on a vector of outcome variables. Second, the synthetic control assumes that the treatment is binary and exogenous, while in this case the treatment is continuous and endogenous. Third, the standard synthetic control model has only one or a small number of treated units; here I have hundreds, so I pool pairs of base counties and their synthetic controls and estimate using weighted 2SLS. Despite the differences, with some abuse of the terminology, I call this way of constructing comparing groups a "synthetic control approach".

This approach has a few advantages over the first approach, which simply includes predetermined covariates. First, this non-parametric approach allows for a county-specific secular trend for each treated unit, which is more flexible than parametric specifications. Since military bases are located in virtually all types of counties, the individual matching approach is arguably more precise than pooled regressions. Second, by constructing a counterfactual based on the trajectories of outcome variables in the pre-treatment period, the chance of mis-specification is lower. In this case, mis-specifying the covariates not only reduces the precision of the estimation, but also invalidates the instrument and results in inconsistent estimates. In Appendix C, I show using a simulation exercise that mis-specifying the secular trend in a parametric way leads to large biases, while non-parametric matching based on pre-treatment trajectories of outcome variables leads to reduced bias in a finite sample. Finally, this approach finds a synthetic county that is similar in many important dimensions of interest, which is conceptually consistent with a "counterfactual" county.

I denote a county group g as the collection of the base county and the counties making up its synthetic control, and estimate the following equation using Weighted Two-Stage Least Squares estimator

$$\Delta y_{khg} \quad = \quad \beta_k \Delta mil_{hg} + \theta_g + \varepsilon_{khg}, \tag{30}$$

with the first stage equation

$$\Delta mil_{hg} = \eta \Delta mil_{hg}^{IV} + \zeta_{hg},$$

where county $h \in I \cup J$ is either a base county or a non-base county and θ_g is a dummy variable that is equal to 1 if county h belongs to county group g. I use weights from the synthetic control and assign counties with military bases weights equal to 1. Each county group thus has a total weight equal to 2. $\Delta mil_h^{IV'} = mil_{h,1987}$ is used as the instrumental variable for Δmil_{hg}^{IV}.

The standard errors of estimating equation 30 should be adjusted for multiple reasons. First, a non-base county can be used multiple times as parts of the synthetic control for different base counties. Second, the fact that a base county and its synthetic control had similar secular trends suggests that they are likely to be affected by similar shocks. Finally, estimation of equation 30 involves using weights in the synthetic control that are constructed from a previous step. Standard errors should be adjusted to reflect the uncertainty in the the way the weights are constructed. I report two sets of standard errors. First, I cluster the standard errors by county (h) and county group (g), using the multi-way clustering technique proposed by Cameron et al. (2011). The two-way clustered standard errors utilize the prior knowledge about the error structure, but do not take into account of the uncertainty of the synthetic control approach in the first step. Alternatively, I bootstrap the whole procedure to conduct statistical inferences.[30] The bootstrapped standard errors incorporate variability from the construction of the weights, but can be less efficient since it does not fully incorporate prior knowledge about the error structure. Nevertheless, both methods give very similar statistical inference.

To illustrate this novel identification strategy that combines synthetic control and weighted 2SLS, figure 2 shows the case of San Diego County, which has the largest number of military personnel in the United States. The four panels in figure 2 show changes in military presence and changes in civilian employment, total civilian earnings, civilian population, and private business establishments for both San Diego and "synthetic San Diego", with the levels in 1980 standardized to 1. Between 1980 and 1987, the ratio of military personnel to 1980 population in San Diego stayed at around 0.08. This number gradually dropped to below 0.06 in 2000. Synthetic San Diego, on the other hand, had military presence close to zero throughout the period. San Diego and its synthetic control exhibit similar trajectories in all four sequences before 1988. After 1988, San Diego experienced slower growth in employment, earnings, population, and the number of business establishments than its synthetic control. The difference between the changes in outcome variables in San Diego and in its synthetic control is attributed to the net

[30] One complete procedure includes (1) re-sampling with replacement separately for the sample of base counties and the sample of non-base counties, (2) constructing synthetic controls for each base county from the pseudo-sample of the non-base counties, and (3) estimating equation 30 and clustering the standard error by county group and county. The standard error from the bootstrap-se procedure is the standard deviation of the estimated coefficients from bootstrapped pseudo-samples. Abadie & Imbens (2008) show that bootstrapping fails for simple nearest neighbor matching. The intuition is that, by restricting the closest comparison units to a fixed small number, bootstrapping fails to generate meaningfully different pseudo-samples. They conjecture that bootstrapping works for kernel density matching since it allows somewhat different comparison units to enter the sample, though the convergence rate is slower. My approach is similar in spirit to kernel density matching in the sense that more similar comparison units are given higher weights and less similar comparison units are given smaller weights. In Appendix D, I show Monte Carlo simulation evidence that bootstrapping leads to a rejection rate that is close to the true rate. In Appendix D, I also compare statistical inferences based on the bootstrap-se procedure and that based on the bootstrap-t procedure.

changes of military presence in San Diego. Any possible correlation between the size of military cut and idiosyncratic shocks is addressed by using the Bartik instrument.[31]

Figure 3 shows that the synthetic control for San Diego closely resembles San Diego in pretreatment trends. In table 1, I report the overall quality of synthetic controls for all base-counties. Each row shows the changes in the outcomes of interest prior to the military cuts. Column 1 reports the changes for base counties, and column 2 reports the changes for non-base counties. On average, base counties were on a better growth path than non-base counties, prior to the cuts. For example, between 1980 and 1987, civilian employment grew by 19 percent in base counties, and only 11 percent in non-base counties. Column 4 reports the $p-$value for the differences between column 1 and column 2, which shows that the differences are always statistically significant at the 1% level. Column 3 shows that the weighted averages of the synthetic counties are very similar to those of the base counties (column 1); the differences are statistically insignificant at any conventional levels, regardless of whether the comparison is made on average (column 5) or within each county pair (column 6).

5 Data and Sample

This paper uses multiple sources of publicly available data. This section briefly introduces data sources and the construction of the main sample. Appendix A has a more detailed description of how the key variables are constructed.

5.1 Data

The Department of Defense (DoD) publishes the distribution of military bases in its annual Base Structural Report (BSR). The BSR from 1989 reports a snapshot of 535 major military bases with at least 250 personnel as of February 1988, eight months before the enactment of the Base Re-alignment and Closure Act. The geographic boundaries for most of these military bases are obtained from a digitalized map called "Military Installations, Ranges, and Training Areas Boundaries", prepared by the DoD and published as part of the National Transit Database in 2011. For the remaining bases, I searched for historical maps as well as web resources including Google Maps and Wikipedia to determine their location and boundaries. I then overlaid the GIS map with the 1989 military bases onto a GIS map of US counties from 1990 Census. I consider

[31] Mathematically, the weighted 2SLS estimation of equation 30 is equivalent to estimating the following equation $(\Delta y_{kc} - \sum_j w_{cj} \Delta y_{kj}) = \beta_k (\Delta mil_c - \sum_j w_{cj} \Delta mil_j) + \Delta \tilde{\varepsilon}_{kcg}$, using the 2SLS with $(\Delta mil_c^{IV'} - \sum_j w_{cj} \Delta mil_j^{IV'})$ as the instrument. Each observation is a county with military bases. Estimating this equation gives results very similar to those from equation 30.

a base county to be any county in which at least parts of its territory intersect with a military base.

The number of military personnel by county in each year comes from the Regional Economic Accounts (REA) published by the Bureau of Economic Analysis, a panel dataset at the county level with annual local economic characteristics. The REA collects data from another DoD annual publication called the Distribution of Personnel, which gives detailed information on DoD employees on military bases and in major cities and converts this into the number of military personnel by county.[32]

The outcomes of interest in this paper capture aspects of the size of the population, and changes in the strengths of the local labor market, local housing market, and local businesses. County population counts are county-level tabulations of decennial censuses, with the number in non-census years interpolated. The REA also reports employment and earnings by 2-digit sectors, from which I calculate total civilian sector employment and earnings. County median rental prices and units of occupied housing also come from county-level tabulations of decennial population censuses. These variables are based on self-reported values of individual households responding to the census. The annual number of private business establishments by 2-digit sectors comes from County Business Patterns.

5.2 Sample

This paper treats counties as local economies since they are the level of aggregation for most of the key variables used in this paper.[33] Due to concerns that military personnel contractions can spill over across county borders, in one of the robustness checks I use commuting zones as the alternative definition of local economies.

The REA groups some neighboring small counties into new county-level units. Throughout the paper I use the REA definition of counties and convert county-level variables from other sources accordingly. To avoid cases in which the military is the only economic activity, I drop counties that had fewer than 5,000 civilians in 1980. I further drop about 10 percent of base counties that actually experienced *increases* in military presence between 1988 and 2000. Since the effects can be asymmetric for expansions,[34] dropping a small number of counties that experienced expansions helps with the interpretation of the estimation results. The final sample has

[32] The Distribution of Personnel reports both military personnel and civilian employees who work on bases. Unfortunately, the REA only separately reports the number of military personnel. Civilian employees of the DoD are grouped into a broader category called federal civilian workers.

[33] Existing studies have used various definitions of local economies, including counties (e.g., Black et al., 2005), commuting zones (e.g., Autor et al., 2013), metropolitan areas (e.g., Moretti, 2010b), and states (e.g., Blanchard & Katz, 1992).

[34] For example, Glaeser & Gyourko (2005) and Notowidigdo (2013) explain for why positive shocks and negative shocks have asymmetric effects.

335 base counties. There are also 2,429 non-base counties prior to matching.

6 Empirical Results

6.1 Comparing Specifications

I estimate various specifications of the baseline model in equation 25 and equation 30, with and without using the Bartik instrument. Table 2 reports these estimates using changes in civilian employment between 1988 and 2000 as the outcome variable. Since both the outcome variable and the key explanatory variable Δmil_c, the 1988-2000 change in military personnel, are scaled by the 1980 population, the coefficient associated with Δmil_c can be conveniently interpreted as the number of civilian jobs lost that is associated with cutting one military person.

I first estimate equation 27 using OLS on a sample of only base counties. I control for a vector of pre-determined county-level economic and demographic characteristics. The results are reported in column 1 of table 2, which shows that cutting one military worker is associated with losing 0.8 jobs in the civilian sector. The estimate is statistically significant at 1% level. The OLS estimate may be inconsistent due to simultaneity bias and omitted variable bias. If the DoD avoided large cuts in counties with negative idiosyncratic shocks, or counties experiencing large cuts had otherwise faster economic growth, the OLS estimate is likely to be biased downwards. Column 2 estimates the same equation as in column 1 but uses the initial military presence ($\Delta mil_c^{IV'}$) as the instrument for the change in number of military personnel. The estimated coefficient is 1.2, and it is statistically significant at the 1% level. The first stage is strong with F statistics of about 60. Consistent with the hypothesized source of endogeneity, the 2SLS estimate is larger than the OLS estimate, although a simple-Hausman test shows that the difference is not statistically significant.[35]

If the covariates included in the regression in column 1 and column 2 mis-specify the secular trend, the estimates could still suffer from omitted variable bias and the instrumental variable would be invalid. Column 3 in table 2 uses the generalized synthetic control method introduced earlier to purge out the secular trends and estimate equation 30 by weighted 2SLS. The weights constructed from the synthetic control approach are used in the regression. The number of observations increases to 19,787 just because each component of the synthetic control is included as an observation, no matter how small a weight it bears in the regression. The weights in each county group sum to 2. The estimated coefficient is about 1.3, similar to that in column 2. I report two sets of standard errors. Standard errors in parentheses are two-way clustered at the county level and the county-group level. Standard errors in curly brackets are the standard de-

[35] When conducting the Hausman test, I use conventional standard errors.

viation of 100 bootstrapped estimates. The two-way clustered standard errors are very similar to those in column 2. Both two-way clustered standard errors and the bootstrapped standard errors give the same statistical inference and are significant at the 1% level.

Column 4 re-estimates equation 30 using weighted 2SLS while controlling for the same set of covariates as in column 2. If the specifications in column 2 and column 3 are both valid, including valid controls will not change the point estimate but only improve the precision of the model. I find an estimated coefficient of around 1.3, and the clustered standard error is slightly smaller than that in column 3. The result in column 4 lends more confidence to the findings in column 2 and column 3. Equation 27 and equation 30 rely on different identification assumptions and use different sources of variation, so the fact that both yield very close results is reassuring. For the remainder of the paper I use the specification in column 3 as the baseline for its flexibility in assumptions and good quality in matching, as argued and demonstrated in subsection 4.2.

The number of additional jobs created or destroyed in the local economy as a result of adding or losing one job is called the local job multiplier. Table 2 column 3 shows that the local multiplier is about 1.3. This number falls within a wide range of estimates from previous studies. Using coal price fluctuations as exogenous shocks, Black et al. (2005) estimate that one coal-mining worker brings an additional 0.35 workers to the local labor market within a four-year period. One possible reason for the small effect might be that fluctuations in coal price was perceived as temporary shocks, so local businesses do not adjust on the extensive margin. Moretti (2010b) finds that one additional job in the manufacturing sector creates another 1.6 jobs in the service industry at the MSA level over a decade, a number much closer to mine. This number rises to 2.5 additional jobs, if the manufacturing job is filled by a skilled worker.

6.2 Local Labor and Housing Markets

Using the same specification as in column 3 of table 2, table 3 reports the estimates on a vector of outcomes regarding local labor and housing markets. Columns 1 through 5 report the effects of military personnel contractions on the levels of local economic activity. Column 1 repeats the estimate on changes in civilian employment. Columns 2 through 5 report the estimates on civilian earnings (in thousands of 2000 dollars), civilian population, the number of private business establishments, and the number of occupied housing units. All these outcome variables are divided by the county population in 1980. Therefore, the coefficients can be interpreted as the changes in levels of each outcome due to cutting one military worker.

The military personnel contractions have sizable effects on levels of civilian employment, earnings, population, and business establishments. Specifically, cutting one military worker causes a reduction of 1.3 civilian jobs (column 1) and 31,000 dollars in earnings (column 2) of civilian workers. It also causes a drop of 3.1 civilians in the local population (column 3). This is a large migration response relative to the impacts on the local labor markets. The result suggests that essentially every individual who lost a job left the local economy with his or her family.[36] The number of local business establishments also declines with local employment. For every 10 military jobs cut, a local business is also lost.[37] All of these estimates are statistically significant.

The military to population ratio in counties with military bases dropped by about one percentage point, on average, during the sample period. At the bottom of each column, I convert the effects to percent changes. Reducing the military to population ratio by one percentage point reduces civilian employment by 2.3 percent, total civilian earnings by 1.8 percent, and the civilian population by 2.9 percent. The fact that the percent decline in employment is greater than the percent decline in total earnings suggests that the jobs lost were relatively low-paying.

Column 6 reports the effect on changes in the ratio of civilian employment to civilian population. Given the large migration response to job losses, it is not surprising that employment to population ratios are not seriously affected. In fact, the estimate is small, statistically insignificant, and has the wrong sign: reducing military to population ratio by one percentage point increases the civilian employment to population ratio by 0.3 percentage points.[38]

The next two columns report the effects on log local prices. Therefore, the coefficients can be conveniently interpreted as semi-elasticities. Column 7 reports the effects on local average wages. Due to data limitations, I calculate local average wages based on county-level variables adjusted by demographic characteristics. First, I calcuate annual raw average wages by dividing total county wages and salary earnings with total county wages and salary employment, both from the REA. I then regress log raw county average wages on a vector of county demographic characteristics. These characteristics include racial compositions (white, black,

[36] According to the 1990 census, each military person has on average 0.7 dependents living in the same household. About 60 percent of the civilian population works in the civilian sector. So a loss 1.2 civilian jobs is associated with 2 civilians. Therefore, cutting one military worker directly affects about 2.7 civilians. A reduction of 3.1 civilians is larger than that back-of-the-envelope calculation.

[37] The effects are concentrated in small firms with fewer than 25 employees.

[38] A natural alternative measurement is unemployment rate. The county-level unemployment rates are from the Local Area Unemployment Series (LAUS) published by the Bureau of Labor Statistics (BLS). Using the unemployment rate has three disadvantages. First, county-level unemployment rates are only available from 1990. Second, county-level unemployment rates are model based, and the model has changed since 2000. Third, since unemployment rates are based on state unemployment insurance claims, it is possible that displaced workers who have migrated are still counted as unemployed in their original counties. Using county unemployment rates as the outcome variable, I find that reducing the military to population ratio by one percentage point increases the unemployment rate between 1990 and 2000 by 0.14 percentage points. The estimate is statistically significant at the 5% level but is very small in magnitude. The average unemployment rate was around 5.4 during the period. About 60% of the population is in the workforce, so an increase in the unemployment rate of 0.14 percentage points roughly corresponds to 0.08 unemployed workers per 100 people. As the same cut reduces the civilian population by 1.3 per 100 people, this suggests that the vast majority of the displaced workers are not unemployed by the end of the sample period.

and other), percent of adults with college degrees, and the quadratic terms of these variables. County demographic characteristics are drawn from decennial censuses. Demographic characteristics in non-census years are interpolated.

Column 7 shows that cutting the military to population ratio by one percentage point reduces the log wage by 0.47 percent. The effect is not statistically significant and is quite small in magnitude: for an average job paying 30,000 dollars a year, a 0.47 percent decline is a loss of 141 dollars per year. Although average wages are potentially measured with a lot of error, the estimated effect is consistent with the estimated effects on other results. First, effects on civilian employment and civilian earnings suggest that the effects on raw average wages are small.[39] Second, the large migration response suggests that workers are rather mobile; large changes in wages will be arbitraged out by large out-migration. Column 8 reports the effects on the median rental price. Cutting the military to population ratio by one percentage point reduces log median rent by 1.3 percent. The decline in rental prices is a result of both lower wages and smaller population. Since wages do not drop by much while many people leave the local economy, it is not surprising that the effect on rental prices is larger than that on wages.[40]

Throughout table 3, I report two sets of standard errors: the two-way clustered standard errors are in parentheses, and the bootstrapped ones are in curly brackets. Both sets of standard errors are very similar and give the same statistical inference, but the bootstrapped standard errors are always slightly smaller. Unless otherwise specified, for the rest of the paper I report only two-way clustered standard errors so as to be conservative about statistical inference.

6.3 Sectoral Composition

The model in section 3 incorporates the tradable and non-tradable sectors and gives different predictions for them under military personnel contractions. According to equation 20, labor demand in the non-tradable sector declines since local wages (w_c), local population (N_c), and the demand shifter for local non-tradable goods (m_c^N) all decline. In contrast, according to

[39] Note that if workers are homogeneous, changes in log wages can be expressed in terms of log changes in total civilian employment and log changes in total civilian earnings, that is $\Delta \ln Wage = \Delta \ln Earning - \Delta \ln Employment$. From column 1 and column 2 in table 3, we have the $\Delta \ln Wage$ due to a one percentage point decline in the military to population ratio equal to (-1.796-(-2.345))=0.549. That is, the wage would *increase* by 0.5 percent. Comparing this result with that in column 5 also suggests that military personnel contractions affect low-skilled workers more severely.

[40] An alternative measure of local housing market conditions is the median housing price. Since conceptually the housing price is just the present discounted value of future rental prices, the percent change in rental prices and housing prices due to the same shock should be the same. Using the same specification, I estimate an effect that cutting the military to population ratio by one percentage point reduces local housing prices by 0.9 percent. Smaller responses in housing prices than in rental prices are often found in the literature, especially when housing prices are self-reported. Because houses are only infrequently transacted, self-reported housing prices may not reflect current housing market conditions (Greenstone & Gallagher, 2008; Busso et al., 2013). Therefore, I use rental prices instead of housing prices.

equation 19, employment in the tradable sector may in fact increase as the firm hires more workers when local labor costs become lower. I therefore investigate separately the impact of military personnel cuts on different sectors. Moreover, I also investigate the effects on the number of federal civilian workers since those eployed by the DoD are directly affected by the downsizing of military operations.

Table 4 reports the results of re-estimating equation 30 using changes in civilian employment in each 2-digit sector as the outcome variables. Column 1 shows that for cutting every four military jobs cut, one federal civilian job is also lost. In the sample base counties in 1988, federal civilian workers account for 2.5% of the total population. Therefore, a one percentage drop in the military to population ratio reduces the average level of federal civilian employment by about 10%, which is shown in the last row of column 1. Column 2 reports the effect on employment in the manufacturing sector, a typical tradable sector, where the military personnel contractions have a small and negative effect and the estimate is not statistically significant. So there is no evidence that local firms in the tradable sector expand their employment. Columns 3 through 5 show the employment responses in non-tradable sectors. I find large and statistically significant effects in the construction and the retail sectors, and a sizable effect on the service sector, although it is not statistically significant. These findings are in agreement with previous studies that have also found that the impacts are concentrated in the local non-tradable sectors and the tradable sector is not affected (e.g., Black et al, 2005).

6.4 Welfare Impacts

I can calculate the magnitude of the welfare changes for workers, landowners, and firms by plugging the empirical results found in the previous section into the expressions for welfare analysis in section 3.6, i.e., equations 22, 23, and 24. In order to calculate the welfare impacts, I first need to calibrate the model parameters involved in these expressions. I choose the values of the relevant parameters from national accounts as well as other studies. The share of expenditure on housing, α, and the share of income spent on non-tradable goods, β, come from the BEA National Income and Product Accounts Tables, $\alpha = 0.18$, $\beta = 0.46$.[41] The share of labor in the non-tradable sector production, h_N, and the share of labor in the tradable sector, h_T, both take the value of 0.7.[42] The constant elasticity of substitution among differential goods is

[41]Source: Section 2: Personal Income and Outlays. Table 2.3.5: Personal Consumption Expenditures by Major Type of Product for 2012 full year. Expenditure on housing includes "Housing and utilities" (line 15). Expenditure on non-tradable goods includes all service items except for housing (lines 15-21). URL: http://www.bea.gov/iTable/iTable.cfm?reqid=9&step=1&acrdn=2#reqid=9&step=3&isuri=1&903=65. Last accessed on Aug 24, 2014.

[42]This value is the commonly used labor's share of national income, e.g., (e.g., Krueger, 1999).

taken from the trade literature: $\sigma^T = 2.2$.[43] With a one percentage point drop in the military to population ratio, the changes in welfare for each agent are

$$\begin{aligned} \Delta V^W &= -0.02\% \ (0.72\%) \\ \Delta V^H &= -3.6\% \ (0.39\%) \\ \Delta V^T &= 0.3\% \ (0.22\%). \end{aligned}$$

That is, the welfare of workers drops by 0.02 percent and the welfare of landowners drops by 3.6 percent, while the welfare of firms in the tradable sector increases by 0.3 percent. Standard errors are reported in the parentheses for each welfare calculation.[44] Only the welfare impact on landowners is statistically significant.

The average decline in the military to population ratio was about one percentage point for counies in the sample over the 1988 to 2000 period. The aggregate welfare impact is small for workers and firms in the tradable sector but substantial for landowners.[45]

7 Adjustment of Local Economies

7.1 Estimating Dynamic Effects

The results thus far show the long-run effects of military contractions.[46] It is also interesting to investigate how quickly local economies adjust to the shocks and achieve new equilibria. For example, although there is little welfare loss for workers in the new equilibrium, if it takes a long time for the local economy to arrive at the new equilibrium, the welfare cost in the transition might still be large.

The existing literature has not reached a consensus on how long it takes for new equilibria to be achieved. Blanchard & Katz (1992) and Feyrer et al. (2007) find that employment levels and

[43]Source: Broda and Weinstein (2006). The median value of 3-digit SITC code for tradable goods. URL: http://www.columbia.edu/~dew35/TradeElasticities/ElasticitiesBrodaWeinstein90-01_SITCRev3_3-digit.xls. Last accessed Aug 24, 2014.

[44]The variance-covariance matrix for the empirical results is obtained by bootstrapping. Denote $b_k = \{\hat{\beta}_k^1, .., \hat{\beta}_k^B\}$ as the vector of estimated coefficients for outcome k from bootstrap. The bootstrapped standard error for the original estimate $\hat{\beta}_k$ is the standard deviation of b_k, σ_{b_k}. Denote b_l as the vector of estimated coefficients for another outcome l, the bootstrapped correlation coefficient between outcome k and outcome l is $cov(b_k, b_l)/\sigma_{b_k} \cdot \sigma_{b_l}$. Appendix Table E1 shows the bootstrapped standard errors for the full vector of outcome variables and their correlation coefficients. The standard errors for welfare calculations are then obtained using the Delta Method.

[45]Appendix E provides a host of robustness checks and estimates heterogeneous effects.

[46]To be precise, the effects shown here are the changes in county outcomes over a 12-year period as a result of military contractions that took place anytime in between. I loosely call these estimates long-run effects. Most of the cuts in military personnel took place between 1988 and 1995, and as I will show in this subsection, the full effects of a particular cut was usually realized within 3 years.

unemployment rates in US states, MSAs, and counties recover from negative shocks within a decade. Bartik (1991) finds a somewhat longer period of recovery. Still other studies (e.g., Yoon, 2014) find that negative shocks can have lasting impacts on local economies.

Ideally, we would have panel data and a one-time shock so that we could capture the dynamic effects of the shock using the impacts of the shock on outcome variable changes over many periods both before and after the shock. In the setting of this study, however, the shocks continued for over a decade and were followed by a different treatment period resulting from the anti-terrorism wars prompted by 9/11. Therefore, including many periods of leads and lags is not feasible. Instead of depicting the full trajectory of dynamic effects, this subsection will address the less demanding question of how many years it takes for a shock's effects to become negligible.

I propose two alternative approaches. First, I estimate a panel model with a few leads and lags. I intend to identify the limits of leads and lags that have any effect on the outcome in the current period. Second, I run long-differenced equations with varying numbers of years in between. As we increase the length of the time period for which the difference is taken, the estimate will eventually converge as the the local economy achieves the new equilibrium, since the inclusion of more years does not make a difference.

In the first approach, I estimate the following regression

$$\Delta y_{khgt} = \sum_{s=t-T}^{t+T} \beta_{ks} \Delta mil_{hgs} + \theta_{gt} + \Delta\varepsilon_{khgt}, \tag{31}$$

where, as earlier, a county h is either a base county or a non-base county. g refers to the county group constructed from the synthetic control approach, and t indexes year. $\Delta y_{khgt} = y_{khgt} - y_{khgt-1}$ is the first-differenced outcome k in county h. The outcomes include civilian employment, earnings, and private businesses. Dynamics of rental price, population, and units of occupied housing are not included since they are only available decennially. $\Delta mil_{hgs} = (Mil_{hgs} - Mil_{hgs-1}) / Pop_{h,1980}$ is the first differenced number of military personnel in the county, scaled by its 1980 population. I include past and future cuts up to two years ($T = 2$) in order to capture the dynamic effects.[47] $\Delta\varepsilon_{khgt}$ is the error term.

Δmil_{hgs} is instrumented using the Bartik instrument as discussed earlier

$$\Delta mil^{IV}_{hgs} = mil_{h,1987} \cdot \frac{NtlMil_s - NtlMil_{s-1}}{NtlMil_{s-1}}. \tag{32}$$

[47] Ideally, I would like to include many leading and lagging terms in order to capture the full dynamic effects. However, including more terms creates two problems. First, the number of observations will be smaller for years between 1988 and 2000. Second, including more leads and lags increases the likelihood of incurring multi-colinearity problems.

$mil_{h,1987} = Mil_{h,1987}/Pop_{h,1980}$ is the initial military presence. $(NtlMil_s - NtlMil_{s-1})/NtlMil_{s-1}$ is the annual percent change in nationwide military personnel. In a dynamic panel setting, the variation of the instrument comes from both cross-county and within-county. Finally, the standard errors are two-way clustered at the county group-year level and at the county level.

Column 1 in table 5 shows the dynamic effects on employment. Changes in employment are mainly effected by changes in military personnel contractions that takes places in the current year (t) and those took place in the year before ($t-1$). Both estimates are sizable and statistically significant. The sum of the effects in these two years (1.35) is close to the overall effect found in the long-differenced specification (1.26). Although the sample does not allow for the inclusion of more lags, a comparison of the dynamic results here with those from the long-differenced specification suggests that a military personnel cut has a permanent effect on the level of employment: the effect takes place within a couple of years after the cut, and there is no evidence of recovery.

Since most of the cuts were planned and anticipated, future cuts could have effects on current employment as people respond to future cuts by chaning current behavior. Contrary to that prediction, I find that military cuts in the next year the the year after ($s = t+1$ and $s = t+2$) have small and statistically insignificant effects. The dynamic effects on civilian sector earnings (column 2) and business establishments (column 3) exhibit similar patterns, although the estimates of the effects on earnings are not statistically significant. I report the Angrist-Pischke partial F statistics to assess the power of instruments for each endogenous variable. The first stages are strong.

The dynamic panel models with leads and lags potentially suffer from colinearity, the many IV problem, and loss of observations with the inclusion of more leading and lagging terms. In the second approach, I estimate a series of long-differenced equations with increasing year gaps and see how long it takes the estimates to converge. Suppose the treatment takes place in year 0; this approach builds the intuition that if the local economy has achieved a new long-run equilibrium, say in year n, we would find the same result by comparing the local economy in year 0 with that in year n, or with any year after n. The smallest year gap for which we observe the long-run effect is likely to be the amount of time it takes the local economy to achieve the new equilibrium. Formally, I estimate variations of the following equation

$$\Delta y_{kcl} = \beta_{kl} \Delta mil_{cl} + \theta_{gl} + \Delta \varepsilon_{kcl}, \tag{33}$$

where $\Delta y_{kcl} = y_{kc,1988+l} - y_{kc,1988}$ and $\Delta mil_{cl} = mil_{c,1988+l} - mil_{c,1988}$, and θ_{gl} are dummies for county-group-year-group dummies. The Bartik instrument, Δmil_{cl}^{IV} is constructed in the same manner. The standard errors are two-way clustered at the county-group-year-group level and the county level. Recall that the cuts in military personnel during the sample period were continuous, which means that cuts in two different periods, Δmil_{cl} and $\Delta mil_{cl'}$, are likely to be positively correlated. For the same reason, Δmil_{cl}^{IV} is also correlated with $\Delta mil_{cl'}$. $\Delta mil_{cl'}$ will be the omitted variables in equation 33, and the 2SLS estimate of equation 33 will be upward biased. The correlation will be smaller when the two periods are further away or when l is larger. Therefore, when $\hat{\beta}_{kl}$ and $\hat{\beta}_{kl'}$ ($l' > l$) are similar, it is evidence that when we look at a long enough period of time, the omitted variable bias is not too much of a concern.

Figure 4 shows the effects with l ranging from 1 to 12. For all three outcome variables, the effects achieve a plateau in about 3 years. This result is consistent with those in table 5 and shows that local economies are relatively quick to adjust to shocks.

7.2 Mobility

The quick adjustment of local economies and the large effects on population after negative shocks are consistent with the high mobility of the US population. During the 1990s, about 3% of the population moved across state borders and about 5% of the population moved across county borders every year (Molloy et al., 2011). Low skilled workers, however, are less mobile and more likely to be affected by local shocks. As a result, the negative demand shocks tend to have longer effects on local economies (Glaeser & Gyourko, 2005; Notowidigdo, 2013; Yoon, 2014).

One explanation for the high mobility found in this paper is that people displaced due to military personnel contractions are more mobile than typical displaced workers. Military workers have little connections to the localities where they serve. Once discharged, they are likely to leave with their dependents, some of whom work in the local economy. Veterans, who tend to cluster near military bases in order to benefit from amenities such as commissaries and post exchanges, also tend to leave as these amenities pull out along with the declining military presence.[48] Some civilian workers employed by the DoD have special skills and need to migrate to find good fits. All of these factors may contribute to the large migration response after military personnel contractions.

I test whether there is something special about military contractions in terms of the resulting migration response by estimating the effects of a different type of shock that is arguably more similar to conventional demand shocks. The post-Reagan military contractions involved not only cuts in military personnel contractions, but also cuts in military procurement contracts awarded to local companies. Unlike military personnel contractions, people affected by mil-

[48] I find reducing one military worker increased about 0.2 new veterans in the county who served during the 1990s. During that period, cutting one military worker on net is associated with about 4 new veterans. So the probability of new veterans staying in the county where they served is as low as 5% (0.2/4). I find that the number of older veterans decrease as military pulls out. In net, I find that the total number of veterans do not increase; the estimate is small and statistically insignificant.

itary procurement reductions are not directly associated with military operations. If indeed military personnel contractions generate particularly high migration responses, we would expect the migration response for each job loss due to military procurement contractions to be lower.

The inclusion of cuts in military procurement contracts to local contractors also serves as a test to check whether military procurement contractions are correlated with personnel contractions. If that is the case, the impacts of personnel contractions found in previous sections are overestimated, and including procurement contractions will significantly reduce the estimates. That said, it is unlikely to be the case, since the spatial distribution of changes in military personnel and those in procurement are not correlated.[49]

I use contract-level data from the Federal Procurement Data System (FPDS) and identify military procurements by restricting procurements to those ordered by the Department of Defense. Since 1969, every contract worth more than 25,000 dollars was recorded. Crucially, the files show the amount of each contract and the county address of the primary contract awardee. I aggregate the amount of procurement to the county-year level. Changes in procurement contractions during the post-Reagan military contractions are measured as $\Delta proc_c = (Proc_{c,98-00} - Proc_{c,86-88})/Pop_{c,1980}$, where $Proc_{c,86-88}$ is the average value of procurement awarded to companies located in county c between 1986 and 1988.[50] $Pop_{c,1980}$ is the county population in 1980. I plug this term in equation 30 and instrument $\Delta proc_c$ with the Bartik instrument

$$\Delta proc_c^{IV} = \frac{Proc_{c,83-85}}{Pop_{c,1980}} \times \frac{Proc_{98-00} - Proc_{86-88}}{Proc_{86-88}},$$

where $Proc_{86-88}$ and $Proc_{98-00}$ are the total amounts of procurement awarded at the beginning and the end of the period, each of which is averaged across threee consecutive years.

Table 6 reports the results. First note that including procurement contractions does not change the estimates on personnel contractions. The two components of post-Reagan military cuts, though connected at the national level, have separate effects on local economies. Angrist-Pischke partial F-statistics are reported for each endogenous variable, and the instruments are strong throughout. Procurement contractions have expected effects, although the coefficients are not always precisely estimated. Most importantly, the migration response is similar for both personnel contractions and procurement contractions. For the former, for each job loss in the civilian sector there are 2.4 civilians leaving the county (3.2/1.3); for the latter, this ratio is

[49] The correlation coefficient is around 0.2. The bulk of the military contracts are for weaponry and equipment. The awardees of these contracts are usually large manufacturing companies located in industrial clusters.

[50] The reason for using a 3-year average is that procurement is a flow variable and is bumpy from year to year. In contrast, the number of military personnel is a stock variable. Changes in military procurement from 1986-1988 compared to 1998-2000 capture the gradual contraction in procurement in the 1990s.

about 2.1. This is evidence that the large response in out-migration is not due to the special characteristics of military personnel contractions.

8 Conclusions

This paper studies the local economic impacts of military personnel contractions in the United States between 1988 and 2000. The contractions had sizable effects on the levels of economic activities in counties with historical military presence. Cutting each military worker resulted in the loss of an additional 1.3 civilian jobs and 0.1 private business establishments, most of which were in the non-tradable sectors and from small businesses. However, local economies adjusted quickly. By year 2000, 2.4 civilian residents had left the county for each civilian job loss. As a result, declines in local wages were small relative to those in rental prices. Quantifying the welfare impacts based on a simple spatial equilibrium framework, I show that negative welfare shocks to workers due to lower local labor demand were largely compensated by substantive declines in local cost of living, while landowners suffer from a large decline in total rents.

Many local economies rely heavily on military spending. There are increasing concerns in these communities in a period of substantial cuts in military spending: the budget sequestration of 2013 planned for a 42 billion dollar cut in military expenditure. In a new military budget plan, the former Secretary of Defense Chuck Hagel proposed to cut the Army to pre-WWII levels.[51] This paper, by exploiting a similar policy in the past, finds that these cuts have distributional effects. On the one hand, the labor market quickly adjusts via labor migration, and the welfare of workers is not affected very much. On the other hand, landowners suffer a large decline in rental revenues as local demand for housing drops and housing stocks are slow to adjust. I also find no effects on government revenue or expenditure, or on Congress incumbents' probability of being re-elected.[52]

Policies targeting particular places in order to promote local economies are popular across the world. State and local governments in the United States spend billions of dollars every year trying to attract new businesses or retain existing ones through various incentives (Story, 2012; Story et al., 2012). At the national level, these policies are only justifiable by agglomeration effects in production or frictions in labor mobility, such that the increases in return due to larger local economy is greater than the gains if the business is located somewhere else. This paper does not explicitly test the effects of the military operations on the productivity of nearby firms, but it finds small frictions in migration across local economies. The effects of these policies are

[51]The Washington Post, Feb 24, 2014. http://www.washingtontimes.com/news/2014/feb/24/chuck-hagel-shrink-army-pre-wwii-levels-report/

[52]Results available upon request.

likely to be consolidated in local land prices instead of being reaped by workers.

This paper makes a few simplifying assumptions. In reality, some households contain both workers and landowners. It is interesting to see the heterogeneous effects on renters and homeowners. Renters have fewer constraints to move, but they also incure a smaller welfare shock if they choose to stay. Another assumption I made is that workers are interchangeable across sectors. The wealth effects due to changes in housing values and the tradeoff between space mismatch and sector mismatch may both affect households' migration decisions, which in turn have implications for impacts on wages and welfare. The simple model introduced in this paper can be extended to trelax these assumptions. Finding invidiual data on home ownership, industry, and migration, and empirically testing the predictions of the enriched model can be interesting future work.

Empirically, I demonstrate that the validity of the widely used shift-share instruments hinges on the assumption that past levels of the treatment variable are not correlated with unobservable secular trends in the outcome variable. Because the location choices of many economic activities are endogenous and can be correlated with expected economic trajectories, this assumption can be violated. To solve this problem, I develop a novel two-step identification strategy combining the synthetic control and the two-stage least square methods. Using information from a pre-treatment period, the synthetic control approach constructs a counterfactual and purges out the unobservable secular trends, conditional on which the shift-share instrument is valid. This approach has general applications in cases where parallel trends are not guaranteed and the instrument is only conditionally valid.

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, *105.490*.

Abadie, A., & Imbens, G. W. (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica*, *74*(1), 235-267.

Abadie, A., & Imbens, G. W. (2008). On the Failure of the Bootstrap for Matching Estimators. *Econometrica*, *76*(6), 1537-1557.

aus dem Moore, J. P., & Spitz-Oener, A. (2012). *Bye Bye, G.I. - The Impact of the U.S. Military Drawdown on Local German Labor Markets.*

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, *103*(6), 2121–2168.

Barro, R. J., & Redlick, C. J. (2011). Macroeconomic Effects from Government Purchases and Taxes. *Quarterly Journal of Economics*, *126*, 51-102.

Bartik, T. J. (1991). Who Benefits from State and Local Economic Development Policies? *Upjohn Press*.

Black, D., McKinnish, T., & Sanders, S. (2005). The Economic Impact Of The Coal Boom And Bust. *The Economic Journal*, *115*(503), 449–476.

Blanchard, O. J., & Katz, L. F. (1992). Regional Evolutions. *Brookings Papers on Economic Activity*, *1992*(1), 1-75.

Bound, J., & Holzer, H. J. (2000). Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s. *Journal of Labor Economics*, *18*(1), 20-54.

Busso, M., Gregory, J., & Kline, P. (2013). Assessing the Incidence and Efficiency of a Prominent Place Based Policy. *American Economic Review*, *103*(2), 897-947.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust Inference with Multiway Clustering. *Journal of Business and Economic Statistics*, *29*(2).

Chodorow-Reich, G., Feiveson, L., Liscow, Z., & Woolston, W. G. (2012). Does State Fiscal Relief during Recessions Increase Employment? Evidence from the American Recovery and Reinvestment Act. *American Economic Journal: Economic Policy*, *4*(3), 118–145.

Diamond, R. (2013). *The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000.*

Feyrer, J., Sacerdote, B., & Stern, A. D. (2007). Did the Rust Belt Become Shiny? A Study of Cities and Countries that Lost Steel and Auto Jobs in the 1980s. *Brookings-Wharton Papers on Urban Affairs*, 41-102.

Glaeser, E. L., & Gyourko, J. (2005). Urban Decline and Durable Housing. *Journal of Political Economy*, *113*(2), 345-375.

Gottlieb, J. D., & Glaeser, E. L. (2008). The Economics of Place-Making Policies. *Brookings Papers on Economic Activity*, *1*, 155-239.

Greenstone, M., & Gallagher, J. (2008). Does Hazardous Waste Matter? Evidence from the Housing Market and The Superfund Program. *Quarterly Journal of Economics*, *123*(3), 951-1003.

Guthrie, S. J. (1995). *Government Policy and Economic Behavior: A Case Study of National Defense*. Unpublished doctoral dissertation, Harvard University.

Hoeting, J. A., Madigan, D., & E., A. (1999). Bayesian Model Averaging: a Tutorial. *Statistical Science*, 382-401.

Hooker, M. A., & Knetter, M. M. (2007). Measuring the Economic Effects of Military Base Closures. *Economic Inquiry*, *39*(4), 583–598.

Hultquist, A., & Petras, T. L. (2012). An Examination of the Local Economic Impacts of Military

Base Closures. *Economic Development Quarterly*, *26*(2), 151–161.

Kline, P., & Moretti, E. (2013). Place based policies with unemployment. *American Economic Review, Papers and Procedings*, *103*(3), 238-243.

Kline, P., & Moretti, E. (2014). People, Places and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs. *Annual Review of Economics*.

Kovak, B. K. (2013). Regional Effects of Trade Reform: What is the Correct Measure of Liberalization? *American Economic Review*, *103*(5), 1960-1976.

Krueger, A. B. (1999). Measuring Labor's Share. *American Economic Review*, *89*(2), 45-51.

Marshall, A. (1890). *Principles of Economics*.

Molloy, R., Smith, C. L., & Wozniak, A. (2011). Internal Migration in the United States. *Journal of Economic Perspectives*, *25*(3), 173-196.

Moretti, E. (2010a). Local labor markets. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4B). North-holland.

Moretti, E. (2010b). Local Multipliers. *American Economic Review, Papers and Procedings*, *100*(2), 373-377.

Moretti, E. (2013). Real Wage Inequality. *American Economic Journal: Applied Economics*, *5*(1), 65-103.

Nakamura, E., & Steinsson, J. (2014). Fiscal Stimulus in a Monetary Union: Evidence from US Regions. *American Economic Review*, *104*(3).

Notowidigdo, M. J. (2013, March). The Incidence of Local Labor Demand Shocks [Computer software manual].

Ramey, V. A., & Shapiro, M. D. (1998). Costly Capital Reallocation and the Effects of Government Spending. *Carnegie-Rochester Conference Series on Public Policy*, *48*.

Roback, J. (1982). Wages, Rents and the Quality of Life. *Journal of Political Economy*, *90*(winter), 1257-1278.

Roback, J. (1988). Wages, Rents and Amenities: Differences among Workers and Regions. *Economic Inquiry*, *26*(1), 23-41.

Rosen, S. (1979). Wagebased Indexes of Urban Quality of Life. In P. N. Miezkowski & M. R. Straszheim (Eds.), *Current Issues in Urban Economics* (p. 74-104). Johns Hopkins University Press.

Serrato, J. C. S., & Wingender, P. (2014). *Estimating Local Fiscal Multipliers.*

Shoag, D. (2012). *The Impact of Government Spending Shocks: Evidence on the Multiplier from State Pension Plan Returns.*

Story, L. (2012). As Companies Seek Tax Deals, Governments Pay High Price. *New York Times*.

Story, L., Fehr, T., & Watkins, D. (2012). *United States of Subsides Searchable. http://www.nytimes.com/interactive/2012/12/01/us/government-incentives.html.*

Suarez-Serrato, J. C., & Zidar, O. (2014). *Who Benefits from State Corporate Tax Cuts? A local Labor Market Approach with Heterogeneous Firms.*

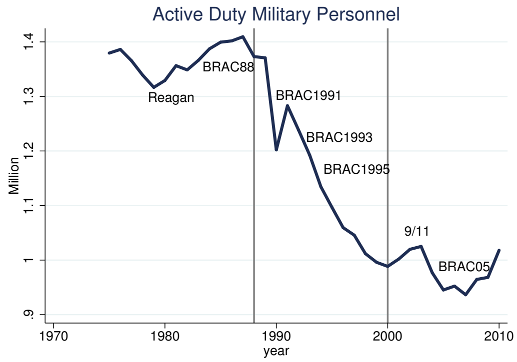
Topel, R. H. (1986). Local Labor Markets. *Journal of Political Economy*, *94*(3), 111-143.

Wilson, D. J. (2012). Fiscal Spending Jobs Multipliers: Evidence from the 2009 American Recovery and Reinvestment Act. *American Economic Journal: Economic Policy*, *4*(3), 251-282.

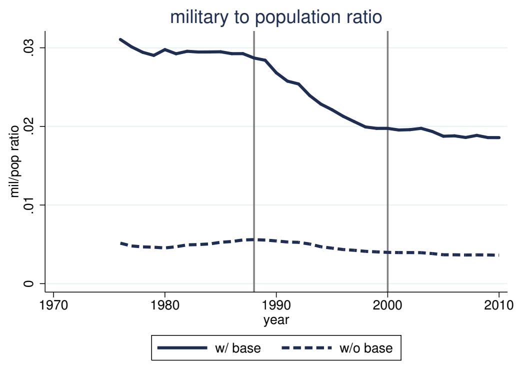
Yoon, C. (2014). *Estimating a Dynamic Spatial Equilibrium Model to Evaluate the Welfare Implications of Regional Adjustment Processes: The Decline of the Rust Belt.*

Figures and Tables

Figure 1: Military Personnel Contractions between 1988 and 2000



B: Change in military to population ratio by county type



Note: Data for figure A are from the annual report of the Distribution of Personnel from the Department of Defense. Active-duty military that deployed in the 50 states and the District of Columbia are included. Figure B shows the change in military to population ratio by whether the county had a major military base in 1987.

Figure 2: Illustration of Workers' Welfare

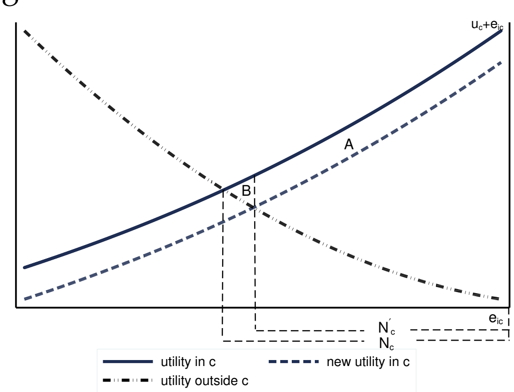
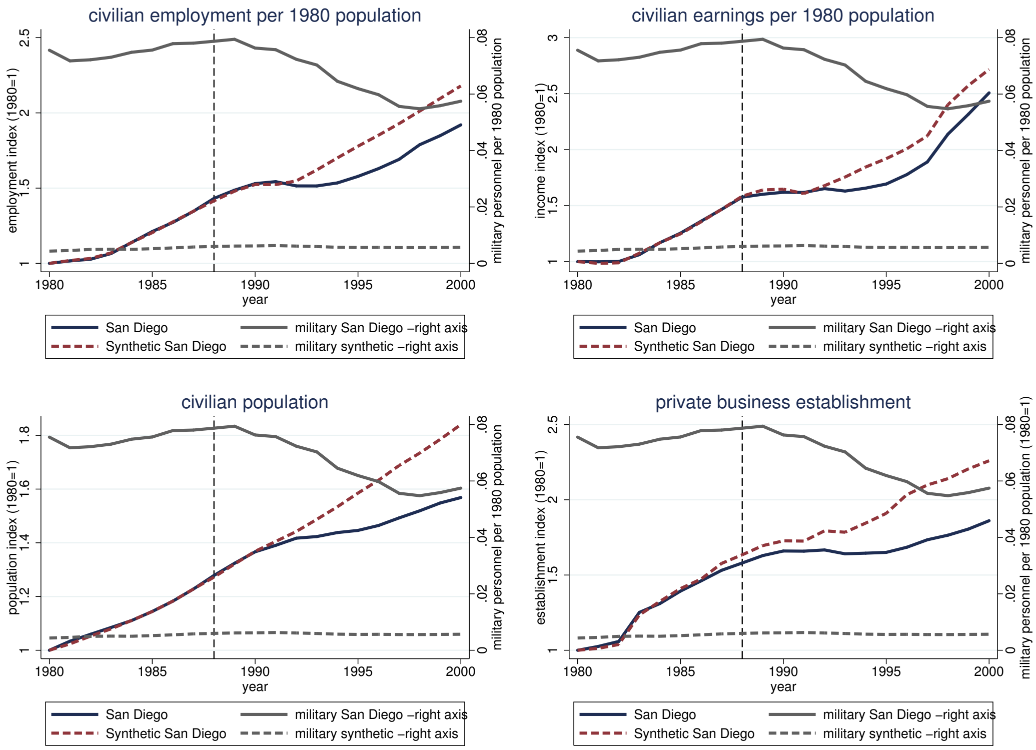


Figure 3: San Diego and Synthetic San Diego



Note: This figure shows an example of San Diego County, California and its synthetic control. The first graph shows the trajectory of civilian sector employment. The second figure shows the trajectory of civilian sector earnings. The third figure shows the trajectory of civilian population. The fourth figure shows the trajectory of private sector establishment. All trajectories are standardized at 1 in 1980. In each panel the gray line shows the trajectory of the military personnel to population ratio.

Figure 4: Accumulative Effects by Grouping Years

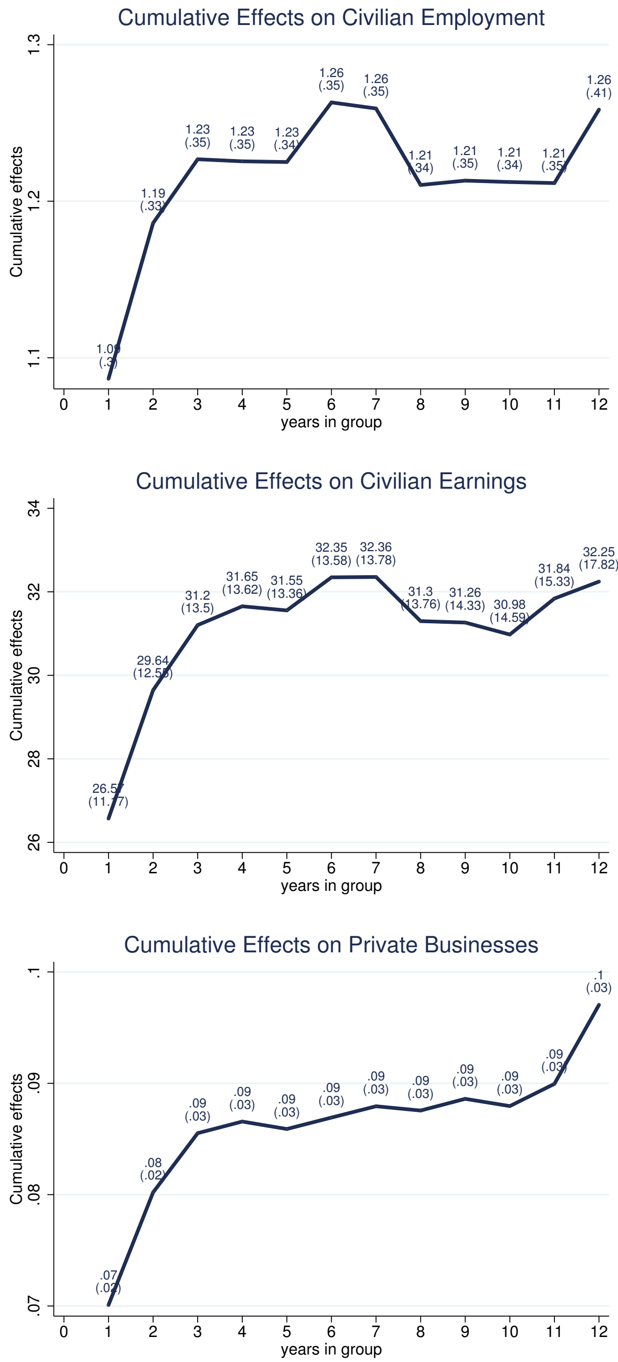


Table 1: Summary Statistics

	Bases	No bases	No bases synth	*p − value* (1)-(2)	(1)-(3)	(1)-(3)
	(1)	(2)	(3)	(4)	(5)	(6)
% change in civilian employment, 1980-1987	.192	.109	.191	0	.909	.671
	(.186)	(.196)	(.204)			
% change in civilian payroll, 1980-1987	.228	.093	.226	0	.946	.792
	(.234)	(.25)	(.265)			
% change in civilian population, 1980-1987	.078	.019	.075	0	.827	.391
	(.098)	(.099)	(.109)			
% change in private establishment, 1980-1987	.340	.211	.341	0	.795	.69
	(.186)	(.099)	(.191)			
log change in median housing price, 1980-1990	.508	.368	.505	0	.916	.775
	(.262)	(.213)	(.309)			
log change in median rental price, 1980-1990	.618	.552	.62	0	.902	.763
	(.157)	(.172)	(.202)			
County-group dummies					N	Y
Number of counties	335	2764	1737	2764	1691	1691
Total weights	335	2764	335	2764	670	670

Note: There are, in total, 2764 counties in the sample that had a civilian population of at least 5000 in 1980. In the first 3 columns, I tabulate average county characteristics for counties with military bases (column 1), counties with no military bases (column 2), and reweighted counties with no military bases on the synthetic approach (column 3). Standard deviations are in parentheses in the first 3 columns. Column 4 reports the $p-$value of the mean difference between columns and column 2. Column 5 reports the $p-$value of the mean difference between columns 1 and 3. Column 6 reports the $p-$value of the difference between counties with military bases and those without while restricting the comparison to be within each treated county and its synthetic cohorts. Predicted changes in county characteristics between 1988 (1990 for housing market outcomes) and 2000 are obtained by running a set of pooled seemingly unrelated regressions using counties without military bases.

Table 2: Military Personnel Contractions and Civilian Employment, 1988-2000

	(1)	(2)	(3)	(4)
Δmil_c	0.793***	1.188***	1.259***	1.266***
	(0.225)	(0.343)	(0.405)	(0.343)
			{0.338}	{0.283}
Covariates	X	X		X
N	335	335	19,787	19,787
Total weights	335	335	670	670
Model equation no.	(27)	(27)	(30)	(30)
Estimation method	OLS	2SLS	2SLS	2SLS
Weights			X	X
First stage F-statistics		58.634	70.688	68.908

Note: The dependent variable is the change in civilian sector employment between 1988 and 2000, scaled by 1980 population. Specification and estimation model are indicated. For weighted regressions, weights constructed from the synthetic control, w_{cj}, are used. For 2SLS estimations, first stage F-statistics are reported. In columns 1 and 2, robust standard errors reported in the parentheses are robust to heteroskedasticity. In columns 3 and 4, standard errors in parentheses are first clustered at the county group level, then clustered at the county level. Significance levels are marked according to the standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. For columns 3 and 4, bootstrapped standard errors are reported in curly brackets.

Table 3: Military Contractions and County Outcomes, 1988-2000

	(1)	(2)	(3)	(4)
	civ emp	civ earning	civ pop	private busi estab
Δmil_c	1.259***	32.245*	3.095***	0.097***
	(0.405)	(17.815)	(0.810)	(0.032)
	{0.338}	{15.243}	{0.691}	{0.025}
percent change with $\Delta mil_c = -0.01$	-2.345	-1.796	-2.903	-3.78

	(5)	(6)	(7)	(8)
	occupied housing units	emp/pop	log wage	log median rent
Δmil_c	0.902***	-0.263	0.468	1.336***
	(0.183)	(0.227)	(0.296)	(0.192)
	{0.162}	{0.222}	{0.259}	{0.179}
percent change with $\Delta mil_c = -0.01$	-2.227	0.438	-0.468	-1.336

Note: Each column uses the outcome variable as indicated in the column headline. In columns 1 through 6 and column 8, the outcome variable is long-differenced between 1988 and 2000. In columns 1 through 4, outcome variables are scaled by 1980 population. Percent changes are reported for columns 1 through 4. Percentages are calculated based on the estimated coefficients and 1988 average levels among base counties. Rental and housing prices use contemporaneous prices. Earnings are in 1000 dollars and are denominated in 2000 dollars. See text for details about the additional covariates. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable, and weights, w_{cj}, are constructed from the synthetic control, as in Column 3 of Table 2. The first-stage F statistic is 70.688. There are 19,787 observations in the sample and 335 county groups. Standard errors are first clustered at the county-group level, then clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors are in curly brackets.

Table 4: Changes in Civilian Employment between 1988 and 2000 by Sector

	(1)	(2)	(3)	(4)	(5)
Emp to 1980 pop by sector	federal civilian	manu	construct	retail	service
Δmil_c	0.251***	0.044	0.204***	0.246***	0.158
	(0.057)	(0.085)	(0.055)	(0.087)	(0.164)
N	19787	19173	18656	19723	19223
First-stage F statistics	70.688	70.282	62.222	70.623	70.051
Mean dependent variable	0.025	0.075	0.031	0.097	0.143
percent change with $\Delta mil_c = -0.01$	10.4	0.57	6.58	2.54	1.10

Note: All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable. The number of observations varies across columns because I drop counties that have a left-censored number of employment in each sector. Standard errors in parentheses are first clustered at the county level, then at the county-group level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Dynamic Effects of Military Personnel Contractions

	(1) emp	(2) earning	(3) estab
$(Mil_{cs} - Mil_{cs-1})/Pop_{c1980}$			
$s = t - 2$	-0.038	9.591	0.041**
	(0.244)	(14.323)	(0.019)
	[23.749]	[23.749]	[23.749]
$s = t - 1$	0.644**	-0.062	0.036**
	(0.277)	(9.339)	(0.017)
	[28.407]	[28.407]	[28.407]
$s = t$	0.714**	15.957	0.022
	(0.281)	(11.159)	(0.018)
	[15.009]	[15.009]	[15.009]
$s = t + 1$	0.017	-2.427	-0.005
	(0.310)	(9.929)	(0.017)
	[12.253]	[12.253]	[12.253]
$s = t + 2$	-0.175	10.185	-0.010
	(0.302)	(10.347)	(0.014)
	[16.411]	[16.411]	[16.411]
obs	257231	257231	257231

Note: Years in the sample are from 1988 to 2000. I use weighted 2SLS estimates in all specifications, as well as weights from the synthetic controls. I include changes in military personnel up to two years before and after the year in question. Outcome variables are the one-year change of the county attributes as indicated by the shorthand on top of each column. Specifically, the outcome variable is annual change in civilian sector employment per 1980 population in column 1; annual change in civilian sector labor income per 1980 population in column 2; annual change in private business establishments per 1980 population in column 3. Standard errors are first clustered at the county-group by year level, then clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The Angrist-Pischke first-stage partial F-statistic for each endogenous variable is reported in brackets.

Table 6: Military Personnel Contractions and Procurement Contractions

	(1) civ emp	(2) civ earning	(3) civ pop	(4) busi estab	(5) log rent	(6) occ houses	(7) log wage	(8) emp pop
Δmil_c	1.317***	29.650	3.217***	0.101***	1.374***	0.937***	0.465	-0.240
	(0.405)	(18.818)	(0.804)	(0.032)	(0.189)	(0.185)	(0.304)	(0.236)
	[72.380]	[72.380]	[72.380]	[72.380]	[72.380]	[72.380]	[72.380]	[72.380]
$\Delta proc_c$	0.075	-3.295	0.156**	0.005**	0.048	0.042*	-0.004	0.030
	(0.049)	(3.445)	(0.070)	(0.002)	(0.046)	(0.023)	(0.046)	(0.023)
	[15.557]	[15.557]	[15.557]	[15.557]	[15.557]	[15.557]	[15.557]	[15.557]

Note: $\Delta Proc_c$ is the change in levels of military procurement between 1986-1988 and 1998-2000 in county i, scaled by 1980 population. Each column uses the outcome variable as indicated in the column headline. There are 19,787 observations in the regression. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable. The Angrist-Pischke partial F-statistic is reported in brackets. Standard errors are reported in parentheses, first clustered at the county level, then clustered at county-group-year level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The Local Economic Impacts of Military Personnel Contractions

Appendices

Appendix A: Sources and Construction of Variables

Key explanatory variable

$mil_{ct} = Mil_{ct}/Pop_{c1980}$ is the military personnel in county c in year t as a ratio to the county's population in 1980. $NtlMil_t$ is the total number of military personnel in the United States (not including those in overseas military bases) in year t. $\Delta mil_c = mil_{c,2000} - mil_{c,1988}$ is the long difference between 1988 and 2000. $\Delta mil_{ct} = mil_{ct} - mil_{ct-1}$ is one-year difference.

Outcome variables

$CivEmp_{ct}/Pop_{c1980}$ is the civilian sector employment in county i in year t divided by the county's population in 1980.

$CivInc_{ct}/Pop_{c1980}$ is the civilian sector earnings (in thousand dollars, 2000 constant dollar) in county c in year t divided the county's population in 1980.

$Wage_{ct}$ is the demographic-adjusted average civilian sector wage in county c in year t. It is calculated as follows. First, average wage per job is calculated as $CivInc_{ct}/CivEmp_{ct}$. It is then regressed on a vector of county-level demographic characteristics, the demographic-adjusted average wage is the residual from the regression.

$CivPop_{ct}/Pop_{c1980}$ is the civilian population in county c in year t as a ratio to the county's population in 1980. Civilian population is total population minus military workers.

$Estab_{ct}/Pop_{c1980}$ is the number of private business establishments in county c in year t divided the county's population in 1980. Private business establishments are from County Business Patterns.

$urate_{ct}$, the unemployment rate in county c in year t, is from Local Area Unemployment Statistics reported by the Bureau of Labor Statistics. County unemployment rates are model-based and are only available sine 1990.

$CivEmp_{ct}/CivPop_{ct}$ is the civilian employment to civilian population ratio in county c in year t.

$MedRent_{ct}$ is the median rental price in county c in year t, and is from county-level tabulations in decennial censuses in 1980, 1990, and 2000.

Other variables

Other county characteristics are from various issues of County Data Books as well as population censuses. These variables include share of white, share of black, share of women, share of population aged between 25-64, share of college graduates, share of high school graduates, share of high school dropouts, share of urban population, county geographic and climatic characteristics, such as population density, average temperature in January, average annual precipitation and snowfall, census regions, etc.

In order to describe the demographic characteristics of the military personnel, including educational attainment, marital status, residence status (live on or off base), characteristics of military spouses (living arrangement, working status, etc), and number of dependents, I use publicly available 5% individual level data of decennial censuses in 1980, 1990, and 2000 from IPUMS. IPUMS data report MSA and state but do not have county identifier. I impute county-level military demographic characteristics by MSA, or by state when the county is not part of any MSA.

Military procurement is from Department of Defense Form DD350, available from 1966 to 2006. DD350 includes all DoD procurement contracts more than 25,000 dollars awarded to the primary contractor. I aggregate the procurement at the county-year level.

Appendix B: Details of the Model

B.1: Household Problem with Unemployment

In this appendix I extend the household problem in section 3.2 to allow for (voluntary) unemployment.[53] Each household now makes a discrete choice of labor market participation. d_{ic} is a dummy variable which is equal to 1 if the household chooses to work, 0 otherwise. Workers have the same productivity if they choose to work. If household i chooses to work, it earns a local wage $\tilde{w}_c$ but derives no utility from leisure; if it chooses not to work, it receives a pecuniary benefit which is standardized to 0, but enjoys a utility from leisure, denoted as l_i.[54] Equally productive workers facing the same labor market conditions have different job market participation decisions due to idiosyncratic preference for leisure. Household i's problem becomes:

$$\max_{h_{ic}, X_{ic}^N, X_{ic}^T, d_{ic}} u_{ic} = \ln A_c + \alpha \ln h_{ic} + \beta \ln X_{ic}^N + (1-\alpha-\beta)\ln X_{ic}^T + l_i \cdot (1-d_{ic}) + e_{ic},$$

$$\text{s.t.}, \; r_c h_{ic} + p_c X_{ic}^N + p_T X_i^T = d_{ic}\tilde{w}_c$$

I assume the distribution of l_i to be independently distributed across locations and is uncorrelated with locational characteristics. I assume that the cumulative density function (c.d.f.) is $L(.)$. The problem for a non-working household and for a working household can be solved in

[53] See also Busso et al. (2013) for a similar treatment of unemployment. Kline & Moretti (2013) introduces involuntary unemployment in the model with matching frictions.

[54] l_i can also be interpreted as distaste for work.

the same way as the problem in section 3.2. Denote $(h^w_{ic}, X^{Nw}_{ic}, X^{Tw}_{ic})$ as the optimal consumption bundle for a working household and $(h^n_{ic}, X^{Nn}_{ic}, X^{Tn}_{ic})$ as the optimal consumption bundle for a non-working household. All these choices are functions of a vector of local prices and model parameters. $u^l_c = \ln A_c + \alpha \ln h^l_{ic} + \beta \ln X^{Nl}_{ic} + (1-\alpha-\beta)\ln X^{Tl}_{ic}$, $l \in \{w, n\}$ is thus the real wage a household gets if it chooses to work, or not. The decision for whether to work is:

$$d_{ic} = \begin{cases} 0, & \text{if } u^w_c < u^n_c + l_i \\ 1, & \text{if } u^w_c \geq u^n_c + l_i. \end{cases}$$

Denote the marginal household with idiosyncratic locational preference for leisure l^*_i which is indifferent between working or not working, this household has utility $u^w_c = u^n_c + l^*_i$. Therefore, households with $l_i < l^*_i$ choose to work, while households with $l_i > l^*_i$ choose not to work. The unemployment rate in location c is

$$urate_c = 1 - L^{-1}(l^*_i).$$

Since l^*_i is a function of local prices $\{\tilde{w}_c, r_c, p_c\}$, which are jointly determined by local economic equilibrium, the unemployment rates are different across locations. However, unemployment rate is determined by other local economic conditions. Having unemployment in the model in this way does not alter the intuition or mechanism of the local economic equilibrium model introduced in in section 3.

B.2: Local Labor Supply

The population size in location c is captured by the preference of the marginal household, e^*_{ic}, in the distribution of e_{ic}. Assuming the total population nationwide is 1. Following the standard result of a type-I extreme value distribution, population size in location c can be written as:

$$N_c = \frac{\exp(u_c/\sigma^W)}{\sum_{c'} \exp(u_{c'}/\sigma^W)}.$$

Take log on both sides, we have equation 2.

B.3: The Tradable Sector

From the firm's profit maximizing problem in equation 8:

$$\max_{N^T_c, K^T_c} \pi_j = p_j x_j - w_c N^T_c - \rho K^T_c,$$

plug in the expression for p_j, and the production function, we have

$$\begin{aligned}\pi_j &= (I_j)^{1/\sigma^T} x_j^{(\sigma^T-1)/\sigma^T} - w_c N_c^T - \rho K_c^T \\ &= (I_j)^{1/\sigma^T} (B_c^T (N_c^T)^{h_T} (K_c^T)^{h_T})^{(\sigma^T-1)/\sigma^T} - w_c N_c^T - \rho K_c^T\end{aligned}$$

First order conditions with regard to N_c^T and K_c^T are:

$$\begin{aligned}&\frac{\partial \pi_j}{\partial N_c^T} = 0 \\ \Rightarrow \quad (I_j)^{1/\sigma^T} \tfrac{\sigma^T-1}{\sigma^T} x_j^{-1/\sigma^T} h_T B_{Tc} (\tfrac{K_c^T}{N_c^T})^{1-h_T} &= w_c\end{aligned} \tag{34}$$

$$\begin{aligned}&\frac{\partial \pi_j}{\partial K_c^T} = 0 \\ \Rightarrow \quad (I_j)^{1/\sigma^T} \tfrac{\sigma^T-1}{\sigma^T} x_j^{-1/\sigma^T} (1-h_T) B_{Tc} (\tfrac{K_c^T}{N_c^T})^{-h_T} &= \rho\end{aligned} \tag{35}$$

Stacking equation 34 and equation 35, we have the marginal rate of substitution between the two factors:

$$\frac{K_c^T}{N_c^T} = \frac{w_c}{\rho} \frac{1-h_T}{h_T} \tag{36}$$

Plug equation 36 back into equation 34, we derive the expression describing the demand for labor in the tradable sector as a function of factor prices and model parameters:

$$\begin{aligned}h_T (I_j)^{1/\sigma^T} \tfrac{\sigma^T-1}{\sigma^T} B_{Tc}^{(\sigma^T-1)/\sigma^T} (\tfrac{1-h_T}{h_T})^{(\sigma^T-1)(1-h_T)/\sigma^T} \rho^{-(\sigma^T-1)(1-h_T)/\sigma^T} w_c^{(\sigma^T-1)(1-h_T)/\sigma^T-1} \\ = (N_c^T)^{h_T/\sigma^T}\end{aligned}$$

Take logs on both sides yields equation 9

$$\ln N_c^T = [(1-h_T)(\sigma^T-1) - \sigma^T] \ln w_c + a_{TL},$$

where

$$\begin{aligned}a_{TL} &= \sigma^T \ln h_T + \ln(I_j) + \sigma^T \ln(\frac{\sigma^T-1}{\sigma^T}) + (\sigma^T-1)\ln B_{Tc} \\ &\quad + (\sigma^T-1)(1-h_T)[\ln(1-h_T) - \ln(h_T)] - (1-h_T)(\sigma^T-1)\ln\rho\end{aligned}$$

Notice that $[(1-h_T)(\sigma^T-1) - \sigma^T] < 0$. The demand for labor in the tradable sector decreases with local wage.

Similarly, plug equation 36 back into equation 35, we derive the expression for demand for capital in the tradable sector as a function of factor prices and model parameters:

$$
\begin{aligned}
&(1-h_T)^{1+h_T(\sigma^T-1)/\sigma^T} h_T^{h_T(\sigma^T-1)/\sigma^T} \rho^{-[1+h_T(\sigma^T-1)/\sigma^T]} \quad (\frac{\sigma^T-1}{\sigma^T}) B_{Tc}^{(\sigma^T-1)/\sigma^T} w_c^{[h-(\sigma^T-1)]/\sigma^T} \\
&\qquad = (K_c^T)^{1/\sigma^T}
\end{aligned}
$$

Take logs on both sides

$$
\ln K_c^T = -(\sigma^T-1)h_T \ln w_c + a_{TK}, \tag{37}
$$

where

$$
\begin{aligned}
a_{TK} &= [(\sigma^T-1)h_T - \sigma^T]\ln\rho + \ln I_j + \sigma^T \ln\frac{\sigma^T-1}{\sigma^T} - \ln B_{Tc} \\
&\quad + h_T \ln(\frac{1-h_T}{h_T}) + \sigma^T \ln(1-h_T) + \sigma^T \ln B_{Tc} + \sigma^T h_T \ln\frac{1-h_T}{h_T}.
\end{aligned}
$$

B.4: The Non-Tradable Sector

In order to derive the labor demand function for the non-tradable sector, we start from the non-tradable firm's profit function in equation 12:

$$
\max_{N_c^N, K_c^N} \pi_c^N = p_c B_{Nc} (N_c^N)^{h_N} (K_c^N)^{1-h_N} - w_c N_c^N - \rho K_c^N
$$

First order conditions with regard to N_c^N and K_c^N are:

$$
\begin{aligned}
&\frac{\partial \pi_c^N}{\partial N_c^N} = 0 \\
\Rightarrow \quad & p_c B_{Nc} h_N (\frac{K_c^N}{N_c^N})^{1-h_N} = w_c
\end{aligned} \tag{38}
$$

$$
\begin{aligned}
&\tfrac{\partial \pi_c^N}{\partial K_c^N} = 0 \\
\Rightarrow \quad & p_c B_{Nc} (1-h_N) (\tfrac{K_c^N}{N_c^N})^{-h_N} = \rho
\end{aligned} \tag{39}
$$

Stacking equation 38 and equation 39, we have the marginal rate of substitution (MRS) between the two factors:

$$
\frac{K_c^N}{N_c^N} = \frac{w_c}{\rho} \frac{1-h_N}{h_N} \tag{40}
$$

Plug the MRS condition back into the production function of local non-tradable goods, we have the supply of local non-tradable goods as a function of local prices and model parameters

$$\begin{aligned}
X_c^N &= B_{Nc}N_c^N(\frac{K_c^N}{N_c^N})^{1-h_N} \\
&= B_{Nc}N_c^N(\frac{w_c}{\rho}\frac{1-h_N}{h_N})^{1-h_N}.
\end{aligned}$$

Take logs on both sides and we get equation 13, where $a_{NX} = \ln B_{Nc} + (1-h_N)[\ln(1-h_N) - \ln(h_N)]$.

Taking logs on both sides of equation 14 and combining it with equation 13 yields equation 15:

$$\ln N_c^N - \ln N_c = h_N \ln w_c + \ln m_c^H - \ln p_c + a_{NL},$$

where $a_{NL} = \ln\beta - \ln B_{Nc} - (1-h_N)[\ln(1-h_N) - \ln\rho - \ln h_N$.

The implications for the zero-profit condition for firms in the non-tradable sector can be derived as follows. Plug equation 40 into equation 12 and require the maximized profit to be zero yields:

$$\begin{aligned}
\pi_c^N &= N_c^N[p_c B_{Nc}(\frac{1-h_N}{h_N})^{1-h_N} - w_c - w_c\frac{1-h_N}{h_N}] = 0 \\
\Rightarrow \quad h_N \ln w_c &= \ln p_c + b_N,
\end{aligned}$$

where $b_N = \ln B_{Nc} + (1-h_N)\ln(1-h_N) + h_N \ln h_N - (1-h_N)\ln\rho$.

Appendix C: Two-Step Estimation of Panel Model with Endogenous Treatment

C1. Data Generating Process

Consider the following data-generating process

$$y_{it} = \beta_0 + \beta_1 X_{it} + f(\lambda_i, t) + \varepsilon_{it}, \tag{41}$$

where i is the index for units and t is the index for time periods, $t \in [1, T]$. X_{it} is the treatment of interest. $f(.)$ is an unknown function of fixed effect λ_i and t. λ_i is unknown to the econometrician.

There is an observable predetermined status $D_i = \{0, 1\}$ which is a function of λ_i and v_i, $D_i = g(\lambda_i, v_i)$. v_i is *iid* and uncorrelated with ε_{it}, $E[v_i, \varepsilon_{it}] = 0$.

X_{it} depends on D_i and is correlated with unobserved determinants of the outcome, and is potentially measured with error:

$$X_{it} = \begin{cases} 0 & \text{, if } D_i = 0 \text{ or } t < t_s \\ \rho_1 \tilde{X}_{it-1} + e_{it} + h(\lambda_i, \varepsilon_{it}, t) + \epsilon_{it} & \text{, if } D_i = 1 \text{ and } t \geq t_s \end{cases}$$

The specification of X_{it} requires some clarification. First, $\rho_1 > 0$ means that X_{it} exhibits positive serial correlation. e_{it} is an classic measurement error with *iid* distribution and mean zero. $\tilde{X}_{it}$ is the deterministic part of X_{it}, $E(\tilde{X}_{it}, \varepsilon_{it}) = 0$. $h(\lambda_i, \varepsilon_{it}, t)$ specifies the endogeneity structure of X_{it}. ϵ_{it} is an *iid* error term, $E[\epsilon_{it}, \varepsilon_{it}] = 0$, $E[\epsilon_{it}, \lambda_i] = 0$, $E[\epsilon_{it}, \tilde{X}_{it}] = 0$. Endogeneity of the treatment, X_{it}, comes from three sources. First, it conditions on D_i, which is determined by λ_i. Second, it is correlated with the unobserved fixed effects λ_i. Third, it is also correlated with the contemporaneous error term ε_{it}.

X^{IV}_{it} is a candidate instrumental variable for X_{it}.

$$X^{IV}_{it} = \begin{cases} 0 & \text{, if } D_i = 0 \text{ or } t < t_s \\ \rho_2 \tilde{X}_{it-1} + \tilde{e}_{it} + \tilde{\epsilon}_{it} & \text{, if } D_i = 1 \text{ and } t \geq t_s \end{cases}$$

$\tilde{e}_{it}$ is another classic measurement error. X^{IV}_{it} is uncorrelated with ε_{it}, $E(X^{IV}_{it}, \varepsilon_{it}) = 0$. But it is conditional on D_i, in other words, $E(X^{IV}_{it}, \lambda_i) \neq 0$. Thus the validity of X^{IV}_{it} as an IV hinges on whether $f(\lambda_i, t)$ can be purged out from equation 41.

Consistency of the conventional panel model hinges on the correctly specifying $f(.)$. Consider the simplest case where $f(\lambda_i, t) = \lambda_i$, the data generating process reduces to:

$$y_{it} = \beta_0 + \beta_1 X_{it} + \lambda_i + \varepsilon_{it}.$$

In a panel fixed effect model, the equation is first demeaned:

$$(y_{it} - \bar{y}_i) = \beta_1 (X_{it} - \bar{X}_i) + \varepsilon_{it},$$

where the condition $\bar{\varepsilon}_i = 0$ is used. $(X^{IV}_{it} - \bar{X}^{IV}_i)$ is thus a valid IV for $(X_{it} - \bar{X}_i)$ in the demeaned equation, as $E[(X^{IV}_{it} - \bar{X}^{IV}_i), \varepsilon_{it}]$. But in general, if $f(.)$ is not a constant, demeaning does not cancel out λ_i and X^{IV}_{it} is invalid.

We construct a synthetic control for each unit i with $D_i = 1$ from a the "donor pool" of units with $D_i = 0$ such that the distance between the trajectory of y_{it} in $t \in [1, t_s]$ and that of its synthetic control y^{synth}_{it} is minimized by solving the following problem:

$$\min_{\alpha_{i_j}} ||\mathbf{Z}_{it} - \sum_j \alpha_{i_j} \mathbf{Z}_{jt}||,$$

where $\alpha_j \in [0,1]$ if $D_j = 0$, and $\sum_j \alpha_{i_j} = 1$. $\alpha_i = 1$ if $D_i = 1$. $\mathbf{Z}_{it} = \{y_{i\tau}, \tau \in [1,s)\}$ is a set of past realizations of the outcome variable before the treatment takes place in period s. According to the data generating process as specified in equation 41, under the optimal weights α_{i_j}, the distance $||f(\lambda_i, t) - \sum_j \alpha_{i_j} f(\lambda_j, t)||$ is also minimized.

If the matching is perfect, $f(\lambda_i, t) - \sum_j \alpha_{i_j} f(\lambda_j, t) = 0$. Counties in the same synthetic control group ($D_i = 1$ and $D_j = 0$) with appropriate weights can be written as

$$\begin{aligned} y_{it} &= \beta_0 + \beta_1 X_{it} + f(\lambda_i, t) + \varepsilon_{it} \\ \alpha_{i_j} y_{jt} &= \alpha_{i_j}[\beta_0 + \beta_1 X_{jt} + f(\lambda_j, t) + \varepsilon_{jt}] \end{aligned}$$

We can purge the secular trend by taking difference between the treated unit and its synthetic control.

$$y_{it} - \sum \alpha_{i_j} y_{jt} = \beta_1 (X_{it} - \sum_j \alpha_{i_j} X_{jt}) + (\varepsilon_{it} - \sum_j \alpha_{i_j} \varepsilon_{jt})$$

We can estimate the following transformation of equation 41:

$$y_{hgt} = \beta_0 + \beta_1 X_{hgt} + \omega_{hgt} + \varepsilon_{hgt}, \tag{42}$$

where county h can be a treated unit i or an untreated unit j, group g includes a unit i with $D_i = 1$ and units j with $D_j = 0$. ω_{igt} is a dummy variable indicating a group-time period. Each equation is weighted by α_h. Demeaning within the group-time period, we have the following

$$(y_{hgt} - \frac{1}{2}\sum_h \alpha_h y_{hgt}) = \beta_1 (X_{hgt} - \frac{1}{2}\sum_h \alpha_h X_{hgt}) + (\varepsilon_{hgt} - \frac{1}{2}\sum_h \alpha_h \varepsilon_{hgt}).$$

Thus $(X^{IV}_{hgt} - (1/2)\sum_h \alpha_h X^{IV}_{hgt})$ is a valid instrumental variable for $(X_{hgt} - (1/2)\sum_h \alpha_h X_{hgt})$ because

$$E[(X^{IV}_{hgt} - (1/2)\sum_h \alpha_h X^{IV}_{hgt}), (X_{hgt} - (1/2)\sum_h \alpha_h X_{hgt})]$$

To sum up, we have a case here where the instrument is only conditionally valid. If the unobserved heterogeneity affects the outcome in the sample period, our instrument is only valid when conditional on the potentially time-varying effects of the unobserved heterogeneity. When the functional form of the time-varying heterogeneous effect is unknown, the synthetic control approach provides a non-parametric way to partial out the effects of the heterogeneous effect.

C2. Analogue

I have a sample of counties (i and j) between 1980 and 2000 (t). Military cuts (X_{it}) started in 1988 (t_s). Only counties with military bases (D_i) are affected. Military bases have been in a county since many periods earlier. Whether having military bases (D_i) and economic outcome (y_{it}) are both determined by some unobservable characteristics of the county (λ_i). The effect of λ_i on the outcome variable can also vary with time in an unknown functional form ($f(\lambda_i, t)$). The size of the military cut in a particular year is correlated with the time-invariant county characteristics and potentially time-varying idiosyncratic shock ($h(\lambda_i, \varepsilon_{it}, t)$), and is measured with error (e_{it}).

C3. Simulation

I simulate the data and demonstrate that the two-step procedure proposed above reduces estimation bias without knowing the functional form of $f(\lambda_i, t)$, while the bias of the standard panel data approach replies on correctly specifying $f(\lambda_i, t)$.

I assume that the unobservable time-invariant county characteristics λ_i is drawn from a Poisson distribution with mean 5 in a sample of $N = 200$. Define $D^* = \lambda_i + v_i$, where $v_i \sim N(0, 5)$. I then sort D^* from the largest to the smallest and assign $D_i = 1$ for the 50 units with the largest D^*. v_i is drawn from a distribution with relatively large standard error such that the group with $D_i = 1$ and the group with $D_i = 0$ have enough overlapping in λ_i. As in a conventional matching approach, overlapping is crucial for the validity of the estimator.

I draw $T = 30$ periods. The treatment period starts since $t_s = 11$. Equation 41 is parameterized as follows: $\varepsilon_{it} \underset{i.i.d}{\sim} N(0, 2)$, $\beta_0 = 3$, $\beta_1 = 1$. $f(\lambda_i, t) = \gamma_1 \lambda_i + \gamma_2 \lambda_i \cdot t$. The endogenous variable, X_{it}, is parameterized as follows:

$$X_{it} = \begin{cases} 0 & \text{, if } D_i = 0 \text{ or } t < t_s \\ \rho_1 \tilde{X}_{it-1} + d_e \cdot e_{it} + h(\lambda_i, \varepsilon_{it}, t) + \epsilon_{it} & \text{, if } D_i = 1 \text{ and } t \geq t_s \end{cases}$$

$e_{it} \overset{i.i.d.}{\sim} N(0, 5)$, ϵ_{it} is from an extreme value distribution. $X_{i1} = 0$. $\rho_1 = 0.95$. Therefore, the shock is most likely to be centered around zero, but there are chances where large shocks, once a shock takes place, it tends to persist. The high serial correlation captures the fact that annual cuts during the Post-Reagan military personnel contractions were rather smooth. The endogeneity structure of the treatment is specified as $h(\lambda_i, \varepsilon_{it}, t) = d_\lambda \cdot \rho_\lambda \cdot t + d_\varepsilon \cdot \varepsilon_{it}$. d_λ, d_ε, d_e are dummy variables that turn on and off endogeneity due to, respectively, unobservable local characteristics, unobservable contemporaneous shocks, and measurement error.

C4. Simulation Results

Results using different estimating approaches when d_λ, d_ε, d_e take different values are reported in table C1. Columns in panel A are estimated using Two-Stage Least Squares (2SLS) estimator in a conventional panel model with unit dummies (hereafter called panel FE model). Columns in panel B are estimated using a two-step approach which involves generating groups and sample weights using the synthetic control approach in the first step and estimate using weighted 2SLS in the second step. Column 1 shows the case with no endogeneity, in which case both panel FE and the synthetic matching methods give consistent results, and the estimated coefficients are close to the true value. When there is secular trend based on unobservable characteristics, panel FE estimate is biased due to mis-specification (panel A, column 2), and estimating the model using 2SLS with the instrument does not make the estimation correct (panel A, column 3). In contrast, the two-step approach, no matter whether the model is estimated using weighted least squares or weighted 2SLS, gives estimates close to the true value (panel B, column 2 and column 3). Column 4 and column 5 estimate a model with both unobservable secular trend and endogenous contemporaneous shocks. Panel FE models, either estimated using OLS or 2SLS, are biased. For the synthetic control approach, the weighted least square estimate is also biased (panel B, column 4), but the two-step weighted 2SLS estimate is close to the true parameter (panel B, column 5). Column 6 and column 7 report results when the endogeneity comes from the unobservable county characteristics, column 8 and column 9 report results when the endogeneity comes from both sources, panel FE models all have results far off from the true value, while the two-step weighted 2SLS estimator obtains results that are similar to the true value.

Appendix D: Statistical Inferences for the Two-Step Estimation

The two-step estimation involves the weights and group dummies constructed from the first step to be used in the second step estimation. The standard errors for the second step estimation do not take into account of the uncertainty in matching in the first step. I use bootstrap to conduct statistical inference. In each bootstrap, a pseudo sample is drawn and the two-step procedure, including constructing the synthetic groups with weights and the subsequent estimation, is carried out. Abadie & Imbens (2006, 2008) note that bootstrap does not work in simple nearest neighbor matching with fixed number of matches since the bootstrapped samples do not achieve the asymptotic distribution of the population. They postulate that the bootstrapping in matching estimates that allows a smoother reweighing function, which include the two-step approach introduced here, are likely to remain valid.

I simulate the data using parameters specified table C1, column 2, specifically,

Table C1: Simulation Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Model	OLS	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Panel A: Panel FE									
X_{it}	1.012	1.869	1.943	0.106	1.961	-0.380	2.725	-0.228	2.705
	(0.027)	(0.071)	(0.100)	(0.021)	(0.253)	(0.110)	(0.314)	(0.065)	(0.333)
N	4000	4000	4000	4000	4000	4000	4000	4000	4000
$\beta_1 = 1$ ($p-$value)	0.647	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Synth reweighing									
X_{it}	0.984	1.034	1.086	0.539	1.141	0.375	1.090	0.352	1.089
	(0.010)	(0.202)	(0.160)	(0.092)	(0.146)	(0.241)	(0.171)	(0.220)	(0.171)
N	137900	137900	137900	137900	137900	137900	137900	137900	137900
Total weight	2000	2000	2000	2000	2000	2000	2000	2000	2000
$\beta_1 = 1$ ($p-$value)	0.112	0.868	0.589	0.000	0.334	0.010	0.600	0.004	0.601
γ_1	0	1	1	1	1	1	1	1	1
γ_2	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
d_e	0	0	0	1	1	0	0	1	1
d_λ	0	0	0	0	0	1	1	1	1
d_ε	0	0	0	0	0	0	0	1	1

Note: Robust standard errors in parentheses, clustered at unit-group and unit levels in Panel B.

$$y_{ht} = 3 + \beta_1 X_{ht} + (\lambda_h + 0.1 \cdot \lambda_h \cdot t) + \varepsilon_{ht},$$

$$X_{ht} = \begin{cases} 0 & \text{, if } D_h = 0 \text{ or } t < t_s \\ 0.95 \cdot X_{ht-1} + \epsilon_{it} & \text{, if } D_h = 1 \text{ and } t \geq t_s \\ 0 & \text{, if } t = 0 \end{cases},$$

$$D = \mathbf{1}\{D* = \lambda_h + v_h \geq \bar{d}\},$$

where $\varepsilon_{ht} \underset{i.i.d}{\sim} N(0,2)$, $v_h \sim N(0,5)$, ϵ_{ht} is from an extreme value distribution. The sample size is $N = 200$. $\bar{d}$ is a fixed value such that there are 50 units with $D_h = 1$. $\beta_1 = 0$. In each simulation, ε_{ht} and v_h are simulated and other variables are generated according to the data generating process.

Since X_{ht} is not correlated with ε_{ht}, I estimate the model using weighted least squares as in table C1, panel B, column 2. In each bootstrap, I redraw with replacement units with $D_h = 0$ and $D_h = 1$ separately such that the pseudo samples have the same number of units as in the original samples. Then I conduct synthetic control and construct the groups (w_{hg}) and weights

(α_{hg}). Finally, I estimate the following regression using weighted least squares:

$$y_{hgt} = \beta_0 + \beta_1 X_{hgt} + \omega_{gt} + \varepsilon_{hgt} \ .$$

I conduct three sets of statistical inference based on pairwise bootstrapping. The first is the conventional $t-$statistics with standard errors clustered at the group and unit level. The second approach involves using the standard deviation of the bootstrapped $\hat{\beta}_1$ as the bootstrapped standard error, then calculating the Wald statistic and conduct statistical inference. The third approach involves bootstrapping the Wald statistic, a pivotal statistic, so that the bootstrapping procedure also provides asymptotic refinement. Specifically, denote the Wald statistics from the original sample for the null hypothesis $H_0 : \beta_1 = 0$ as $w_0 = \hat{\beta}_1 / se(\hat{\beta}_1)$. Then for each bootstrap, calculate the Wald Statistics $w^b = (\hat{\beta}_1^b - \hat{\beta}_1)/se^b(\hat{\beta}_1)$. I rank w^b's from the smallest to the largest. Denote the 2^{nd} percentile as w^b_{p2} and the 98^{th} percentile as w^b_{p98}. If $w^b \in [w^b_{p2}, w^b_{p98}]$ then we cannot reject H_0. If $w^b \notin [w^b_{p2}, w^b_{p98}]$ then we reject H_0.[55]

I use three different estimation models. The first model uses the correctly specified model - in this case panel OLS with county fixed effect and county-specific time trend. The second model uses a mis-specified model, in this case panel OLS with unit fixed effects. The third estimation uses the proposed two-step approach. For each estimation model, I calculate the average bias of the estimation, and the rejection rate at 4% level based on (1) the cluster-robust standard errors from OLS, (2) Wald statistics using $\hat{\beta}_1^0 / sd(\hat{\beta}_1^b)$, where $sd(\hat{\beta}_1^b)$ is the standard deviation of estimates from bootstrapped sample, and (3) whether the $w^b \notin [w^b_{p2}, w^b_{p98}]$. Table D1 reports the results.

Findings based on table D1 are as follows. First, OLS with the incorrect specification is clearly biased and inconsistent. The two-step identification strategy gives estimates that are close to the real vlue. The degree of bias depends on the effects of the unobserved heterogeneity can be purged, which in turn relies on the match quality. The quality of match relies on the overlapping of the distribution of λ_h from the group of units with $D_h = 1$ and the group of units with $D_h = 0$. As in the simulation exercise, $D_h = g(\lambda_h, v_h)$. v_h is *iid* and uncorrelated with ε_{ht}, $E[v_h, \varepsilon_{ht}] = 0$. Matching quality will be better if the standard deviation of v_h is large comparing with the standard deviation of λ_h, which generates sufficient overlap of λ_h among the treated units and the untreated units. Second, the correctly specified OLS estimate is less biased than the two-step approach based on the synthetic control, but not by much. The standard errors are larger in the synthetic control approach than that in OLS due to many more control variables. Thus the statistical inference based on the Wald statistic from cluster-robust standard errors in the OLS is under-rejected.

[55] The reason for using the 96^{th} confidence interval instead of the conventional 95^{th} is because I only conduct 100

Table D1: Bias and Rejection Rate by Estimation Model

			Rejection rate at $\alpha = 0.04$ based on		
Model	S	$bias(\hat{\beta}_1)$	$w_0 = \hat{\beta}_1^0/se(\hat{\beta}_1^0)$	$w_B = \hat{\beta}_1^0/sd(\hat{\beta}_1^b)$	$w_0 \notin [w_{p2}^b, w_{p98}^b]$
Panel corrected specified	100	0.002	0.04	0.06	0.06
Panel incorrectly specified	100	0.699	1	1	1
Synthetic	100	0.034	0	0.067	0.083

Note: 100 bootstrap routines are conducted.

Appendix E: Robustness and Heterogeneous Effects

E1. Robustness Checks

Panel model with county dummies

A conventional approach to deal with unit-specific time trend in a differenced equation is to include set of unit dummies. Notice that it is impossible to include county dummies in the baseline model in equation 25, as each county has only one observation. However, we can include the pre-treatment period, and estimate the following equation:

$$\Delta y_{cp} = \beta \Delta mil_{cp} + \lambda_c + \tau_p + \Delta\varepsilon_{cp}, \tag{43}$$

where each c is a base county. p indicates one of the two periods, the pre-treatment period between 1980 and 1987, and the post-treatment period between 1988 and 2000. λ_c is a set of county dummies and τ_p is a dummy indicating the post-treatment period. The instrument for Δmil_{cp} is

$$\Delta mil_{cp}^{IV} = (Mil_{c,1980}/Pop_{c,1980}) \cdot (NtlMil_{\bar{p}} - NtlMil_{\underline{p}})/NtlMil_{\underline{p}},$$

$\underline{p}$ and $\bar{p}$ indicates the first year and the last year in the period, respectively.

Equation 43 allows the secular trends to be county-specific, but assumes that the trends to be linear throughout both periods. The model is identified by the deviation in the changes and the predicted changes in military personnel (IV). Notice that the first component, the pre-existing military presence, is time-invariant, the model is identified by the variation in the second component, the changes in national total military personnel. If the variation of the instrumental variable mainly comes from the differences in pre-existing military presence, the first stage is likely to be weaker in estimating equation 43. Table E2 shows that it is indeed the case. The first stage F statistics is only about 3. Although the estimated coefficients stay largely the same as in table 25, the standard errors are much larger and many of the coefficients are not statistically significant.

bootstraps.

Parallel to equation 31, I estimate a first-differenced panel model with leads and lags in military cuts in order to study the dynamic effects:

$$\Delta y_{ct} = \beta \Delta mil_{ct} + \lambda_c + \tau_t + \Delta\varepsilon_{ct}, \tag{44}$$

where Δ indicates first differences. Similarly, the instrumental variable for Δmil_{ct} is

$$\Delta mil_{ct}^{IV} = (Mil_{c,1980}/Pop_{c,1980}) \cdot (NtlMil_t - NtlMil_{t-1})/NtlMil_{t-1}.$$

The results are reported in table E3 exhibit the same patterns: the estimates are smaller and somewhat less precisely estimated as those in table 5.

Influential counties

One assumption needed for the validity of the instrumental variable is that the national military contractions were not driven by the unobservable economic shocks in some particular local economies. A hypothetical, though unlikely, example of this case is that some local interest groups regard the existence of military bases as detrimental to their local economies, and they lobby for national military cuts. To rule out this possibility, I identify three sets of counties that are most likely to have the incentive and capability to have influenced the national policies: base counties in the Washington, DC area, counties with the largest military bases, and counties that are from districts that were formerly represented by key decision makers in the BRAC commission.[56] The sample in panel A of table E4 excludes the 27 base counties in the DC area. The sample in panel B excludes the top 5 percent counties with the largest military bases. The sample in panel C excludes 25 counties that potentially have political influences. Overall the results are remarkably similar to the baseline results in table 3.

Geographic aggregation

People may work, live, and consume in different counties, the boundaries of local labor markets can be larger than counties. The impacts of military personnel contractions in a larger geographic area can be either larger or smaller than those using counties as local economies. The reason is both economic and statistical. In terms of economics, the impacts are likely to be larger in a larger geographic aggregation if there are spillover effects across county borders. On the other hand, a larger geographic aggregation may internalize local economic impacts, which leads to smaller estimates. For example, in the extreme case, if we define the entire United States as a local labor market, there will be little migration response to demand shocks. Statistically, using larger geographic aggregation may either alleviate or exacerbate the measurement error problem. Aggregation cancels out measurement error, while converting some county-level outcomes into larger geographic aggregations incur additional measurement er-

[56] These people include Speaker of the House, House Minority Leader, members of the BRAC commission.

ror. Military contractions at a larger geographic level are also more likely to be endogenous, as a large local economy can influence national policies. Finally, larger aggregations result in a smaller donor pool, the matching bias from the synthetic matching approach is likely to be larger and the two-step identification strategy more likely to lead to inconsistent estimates.

I use 1990 commuting zones as an alternative definition of local economies. The commuting zones are developed by the Department of Agriculture according to commuting patterns. The 741 commuting zones in 1990 cover the entire United States. On average a commuting zone is about four times as large as a county. I call a "base commuting zone" if the commuting zone intersected with at least one military base in 1987, and the remaining commuting zones form the donor pool. Commuting zone level outcomes are either aggregated from county level variables (for employment, income, population, housing units, etc) or are averages using county population as weights (for median rental price, etc). I identify 208 commuting zones with military bases and saw military presence decline during the 1988-2000 period. I then construct a synthetic control for each base commuting zone from the donor pool. The instrument for military contractions in each commuting zone is the a Bartik instrument constructed in the same way as in equation 26. Finally I estimate equation 30 using the commuting zone sample.

Table E5 shows the results using the same specification and outcome variables as in table 3. The estimated impacts of military personnel contractions are in many cases much larger than those at the county level. For example, cutting one military worker makes the commuting zone to lose about 2.9 civilian jobs, more than twice of the estimate at the county level. The migration response is smaller due to larger geographic area: for each civilian job loss, 1.3 civilians leave the commuting zone. For one percentage decrease of military to population ratio, average wage drop by 0.95 percent, though not statistically significant. The rental price drops by 3.7 percent, also much larger than the effect found using the sample of counties.

E2. Heterogeneous Effects

By the size of the cut

So far the results show that although military personnel contractions have sizable effects on the levels of local employment and population, the welfare impacts are small, and local economies adjust quickly. This finding may mask the non-linear effects of negative shocks. In particular, a local economy may be resilient to small shocks, but large shocks can kick off chain effects causing the local economy on a downward spiral.

In this subsection I investigate non-linearity in the treatment effects by dividing the sample by the size of the cut. Panels A through C in table E6 reports the results of replicating table 3 using base counties (and their synthetic controls) that experience military personnel contractions above the 25^{th}, 50^{th}, and 75^{th} percentile of the distribution. For base counties that are above the

25^{th} percentile, the average size of military personnel contractions accrue to 1 percent of its 1980 population. For base counties that are above the 75^{th} percentile, that it is 3 percent, or close to 6 percent of its 1980 workforce. It is a substantial shock by any standard. Somewhat surprisingly, all three panels give very similar results, which are also close to those in table 3. It seems that the effects of military contractions are close to linear.

By population density

Local economies differ in various dimensions, such that a same degree of military cuts may have different effects across local economies. I investigate the heterogeneous effects by population density of the local economy. I use population density to proxy for the richness of local labor markets in terms of alternative job opportunities. Studies have found that urban local labor markets are more resilient to shocks, we would expect that local labor market outcomes would be less negatively affected in counties with high urban rate.

I divide base counties into two groups, one with the 1987 population density above median and the other below. I repeat the estimates in table 3 separately for the two samples. Table E7 shows the results. The first stage is equally strong in both sub-samples, so the models are well identified. The impacts on employment and population in more densely populated counties are slightly smaller than that in less densely populated counties (column 1 and column 3), and the impacts on civilian earnings, wage and local businesses are larger in less densely populated counties (column 2, column 4, and column 7). Thus it seems that local labor markets in more densely populated areas weather shocks better. Rental price also drops less in more densely populated counties.

Table E1: Variance and Correlation Matrix from Bootstrapping

	emp	earning	pop	estab	occupied houses	emp/pop	ln(wage)	ln(rent)
emp	1							
earning	.821	1						
pop	.698	.476	1					
estab	.798	.682	.786	1				
occupied housing	.663	.516	.696	.635	1			
emp/pop	.164	.043	-.412	-.223	-.128	1		
ln(wage)	.129	.218	.013	.103	.112	0.068	1	
ln(rent)	.323	.189	.399	.285	.109	-.198	.05	1
bootstrap s.e.	.338	15.243	0.691	0.025	0.163	0.222	0.259	0.179

Table E2: Panel Regressions with County Fixed Effects, 1980-2000

	(1) emp	(2) inc	(3) pop	(4) house price	(5) estab	(6) occ house
Δmil_{ct}	1.394	84.085	3.162**	1.900	0.014	1.159**
	(0.861)	(49.968)	(1.573)	(2.395)	(0.022)	(0.573)
County FE	X	X	X	X	X	X
Period FE	X	X	X	X	X	X
N	762	762	762	762	762	762
First Stage F	3.007	3.007	3.007	3.007	3.007	3.007

Note: Standard errors in parentheses, clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table E3: Dynamic Effect of Military Personnel Contractions
Dynamic panel with county fixed effects

	(1) emp	(2) earning	(3) estab
$(Mil_{cs} - Mil_{cs-1})/Pop_{c1980}$			
$s = t - 2$	-0.059	21.532	0.004
	(0.146)	(14.461)	(0.012)
	[23.036]	[23.036]	[23.036]
$s = t - 1$	0.161	10.667	0.003
	(0.174)	(9.616)	(0.009)
	[36.739]	[36.739]	[36.739]
$s = t$	0.422**	9.978	0.014
	(0.207)	(14.159)	(0.011)
	[17.667]	[17.667]	[17.667]
$s = t + 1$	-0.137	-17.431	-0.009
	(0.241)	(10.812)	(0.009)
	[10.241]	[10.241]	[10.241]
$s = t + 2$	-0.052	-9.572	0.001
	(0.188)	(13.837)	(0.009)
	[21.165]	[21.165]	[21.165]
County FE	X	X	X
obs	4355	4355	4355

Note: Years in the sample are from 1988 to 2000. All columns control for county dummy variables and are estimated using the 2SLS estimator. I include changes in military personnel up to two years before and after the current year. Outcome variables are the one year change of the county attributes as indicated by the short-hand on top of each column. Specifically, the outcome variable is annual change of civilian sector employment per 1980 population in Column 1; annual change of civilian sector labor income per 1980 population in Column 2; annual change in private business establishments per 1980 population in Column 3. Standard errors are clustered at the county level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Angrist-Pischke first stage partial F-statistics for each endogenous variable is reported in brackets.

Table E4: Influential Counties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	civ emp	civ earning	civ pop	busi estab	log rent	occ houses	log wage	emp pop
Panel A: exl. DC area								
Δmil_c	1.191***	33.092*	3.346***	0.106***	1.366***	0.921***	0.491	-0.492**
	(0.436)	(19.084)	(0.882)	(0.036)	(0.186)	(0.189)	(0.319)	(0.213)
N	18579	18579	18579	18579	18579	18579	18579	18579
# of base counties	308	308	308	308	308	308	308	308
first stage F	49.8	49.800	49.8	49.8	49.8	49.8	49.8	49.8
Panel B: exl. largest bases								
Δmil_c	1.076***	29.663	2.662***	0.082***	1.485***	0.913***	0.632*	-0.282
	(0.373)	(18.457)	(0.671)	(0.026)	(0.206)	(0.204)	(0.371)	(0.224)
N	18885	18885	18885	18885	18885	18885	18885	18885
# of base counties	319	319	319	319	319	319	319	319
first stage F	76.973	76.973	76.973	76.973	76.973	76.973	76.973	76.973
Panel C: exl. politically connected								
Δmil_c	1.279***	32.286*	3.112***	0.098***	1.323***	0.901***	0.469	-0.261
	(0.411)	(17.634)	(0.820)	(0.033)	(0.193)	(0.185)	(0.295)	(0.230)
N	17912	17912	17912	17912	17912	17912	17912	17912
# of base counties	310	310	310	310	310	310	310	310
first stage F	69.272	69.272	69.272	69.272	69.272	69.272	69.272	69.272

Note: Each panel includes a sample as indicated. Each column uses the outcome variable as indicated in the panel headline. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable. Number of observations, number of county groups, first stage F- statistics are reported. Standard errors in parentheses are first clustered at the county level, and then clustered at the county group level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E5: Commuting Zones

	(1) civ emp	(2) civ earning	(3) civ pop	(4) private busi per capita
Δmil_z	2.885***	50.942	3.886**	0.235***
	(0.999)	(44.762)	(1.510)	(0.070)
	(5) occupied housing units	(6) civ emp pop	(7) log wage	(8) log median rent
Δmil_z	1.525***	0.104	0.949	3.660***
	(0.529)	(0.329)	(0.777)	(0.983)

Note: Each column uses the outcome variable as indicated in the column headline. There are 16,721 observations and 208 commuting zones (indexed by z) with military bases. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable and weights constructed from the synthetic matching. First stage F statistics is 72.877. Standard errors in parentheses are first clustered at the commuting zone level, then clustered at the commuting zone group level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E6: Heterogeneous Effects by the Size of the Cut

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	civ emp	civ earning	civ pop	busi estab	log rent	occ houses	log wage	emp pop
Panel A: cuts $\geq 25^{th}$ percentile								
Δmil_c	1.326***	36.319**	3.025***	0.100***	1.342***	0.922***	0.457	-0.240
	(0.403)	(17.483)	(0.803)	(0.032)	(0.192)	(0.182)	(0.296)	(0.226)
N	16848	16848	16848	16848	16848	16848	16848	16848
# of base counties	270	270	270	270	270	270	270	270
first stage F	72.394	72.394	72.394	72.394	72.394	72.394	72.394	72.394
Panel B: cuts $\geq 50^{th}$ percentile								
Δmil_c	1.340***	38.090**	3.002***	0.100***	1.344***	0.926***	0.459	-0.254
	(0.405)	(17.726)	(0.802)	(0.032)	(0.192)	(0.182)	(0.295)	(0.226)
N	11695	11695	11695	11695	11695	11695	11695	11695
# of base counties	180	180	180	180	180	180	180	180
first stage F	72.044	72.044	72.044	72.044	72.044	72.044	72.044	72.044
Panel C: cuts $\geq 75^{th}$ percentile								
Δmil_c	1.300***	38.455**	2.959***	0.094***	1.275***	0.850***	0.352	-0.276
	(0.390)	(16.872)	(0.770)	(0.031)	(0.184)	(0.162)	(0.282)	(0.221)
N	5996	5996	5996	5996	5996	5996	5996	5996
# of base counties	91	91	91	91	91	91	91	91
first stage F	72.858	72.858	72.858	72.858	72.858	72.858	72.858	72.858

Note: Each panel includes a sample as indicated. Each column uses the outcome variable as indicated in the panel headline. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable. Number of observations, number of county groups, first stage F- statistics are reported. Standard errors in parentheses are first clustered at the county level, and then clustered at the county group level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E7: Heterogeneous Effects by Population Density

	(1) civ emp	(2) civ earning	(3) civ pop	(4) busi estab	(5) log rent	(6) occ houses	(7) log wage	(8) emp pop
Panel A: high population density								
Δmil_c	1.103*	2.570	2.793***	0.063*	0.917***	1.147***	0.370	0.009
	(0.598)	(27.972)	(1.032)	(0.036)	(0.293)	(0.380)	(0.424)	(0.471)
N	11031	11031	11031	11031	11031	11031	11031	11031
First Stage F	42.647	42.647	42.647	42.647	42.647	42.647	42.647	42.647
Panel B: low population density								
Δmil_c	1.338***	47.402**	3.249***	0.114***	1.550***	1.168***	0.518	-0.403*
	(0.498)	(21.479)	(1.065)	(0.040)	(0.213)	(0.317)	(0.376)	(0.237)
N	8756	8756	8756	8756	8756	11031	11031	11031
First Stage F	38.415	38.415	38.415	38.415	38.415	42.647	42.647	42.647

Note: Each column uses the outcome variable as indicated in the column headline. Panel A includes base counties that have 1986 population density above the median, panel B includes those with 1986 population density below the median. All columns are estimated using the weighted 2SLS estimator using the predicted military personnel contractions as the instrumental variable. First stage F statistics are reported. Standard errors are reported in parentheses, first clustered at the county level, then clustered at county-group-year level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.