The Impact of a Local Human Capital Shock: Evidence from World War II Veterans*

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Abstract

As a result of the GI Bill, returning World War II veterans were generally highly educated, but their locations after the war were highly uneven across cities in the US. Exploiting the spatial variation in the returning veterans driven by the prewar communities of veterans, I study the long run persistence of an increase in the local human capital. While there is strong persistence in skills across cities, the shock produced a large and uneven increase in local skills after the war. Furthermore, this positive shock had long-lasting effects on the local human capital during 1940–2010.

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1 Introduction

The distribution of human capital across cities in the US is highly uneven. While urban cities tend to have a higher share of skilled individuals than rural areas do, there is also significant heterogeneity within urban areas. For example, according to American Community Survey (ACS) 5-Year data (2013-2017), the share of people with a bachelor's degree or higher in San Francisco is greater than 47%, whereas, in Fresno, only 20% of the population have a bachelor's degree. Given these striking differences in local skills, economists know relatively little about why and when these differences arise.

It is important to identify the cause of these differences in local skills because the local skill composition of workers has been known to be a strong predictor of local economic growth and development (Glaeser, 1994; Glaeser et al., 1995; Simon, 1998; Black and Henderson, 1999; Simon and Nardinelli, 1996, 2002). For more than a century, cities with educated people have grown more quickly than comparable cities with less human capital (Glaeser and Saiz, 2003). Furthermore, Moretti (2012) recently argues that the innovation and creativity driven by well-educated workers are the main drivers of the *great divergence*, which describes the increasing split between regions that flourish and regions that fail.

One possibility for the cause of this uneven distribution in the local human capital might be a local supply shock of highly educated people in earlier history because the local skill composition is known to be persistent over time (Moretti, 2004a). In other words, cities that had a relatively higher fraction of educated individuals in the past are likely to have a higher share of skilled people at present. Therefore, if there was a historical shock that significantly reshuffled the human capital across cities, the current skill inequality across local economies could reflect the persistence of this shock. In this sense, Allen and Donaldson (2018) explain that the locations of economic activities in the US today are affected by larger historical shocks.

The return of World War II (WWII) veterans following the war can be viewed as one such shock. Because of the GI Bill that provided unprecedented federal support for higher education to returning veterans, a large number of WWII veterans received college education. As a result, the fraction of college educated people was much higher for veterans than for other groups such as nonveteran men or women. Although the GI Bill was national in scope, the variation in returning WWII veterans was highly unequal across cities. While the mean population share of WWII veterans is 14 percent, this ranges between 6 to 24 percent across areas in the US. This uneven geographic distribution of veterans significantly reshaped the distribution of the local human capital across cities in 1950. The mean share of college educated men increased from 11.3 percent to 17.4 percent, and the standard deviation increased from 0.048 to 0.084.

However, the variation in returning WWII veterans across cities may not be exogenous to other local shocks because of the migration of veterans. After the war, they had to choose where to receive college education and then relocate to find jobs after finishing their education. Accordingly, the distribution of WWII veterans could be correlated with other unobserved local characteristics and demand shifts during the period. In other words, the veteran-driven shock could simply be a continuation of local trends. Furthermore, the location choices of the returning veterans could be affected by those of nonveterans. Therefore, exploiting exogenous variation is crucial to estimate the short and long run consequences of this historical shock.

In the prewar period of 1930, there were communities of veterans in some local areas. Because of the network of veterans, this predetermined distribution of veterans in 1930 is a strong predictor for the distribution of WWII veterans in 1950. Using this fact, I construct an instrument that predicts the relative growth of college educated of WWII veterans. The use of this instrument is particularly relevant because veterans in 1930 did not receive any educational benefits; thus, their distribution is less likely to be correlated with the pre-trends in local schooling. As expected, this instrument is not significantly correlated with the pre-1940 change in skill composition. Moreover, the instrument is not correlated with the pre-period changes in population, total employment, and manufacturing employment.

Exploiting the variation in the relative growth of college educated WWII veterans during 1940–1950, driven by the historical cluster of veterans in 1930, I present the consequences of the local human capital shock in the short and long runs. In the short run, the shock significantly lowered the relative growth rate of high skilled nonveteran men and insignificantly increased that of women. This is mainly due to the different occupational specialization between men and women. As a result, the impact on *overall* relative growth rate of college educated workers because of the shock was substantial: a 1-percentage point larger veteran-driven shock leads to a 0.9-percentage point increase in the overall relative growth rate of skill in local economies.

Furthermore, in the long run, this shock continued to attract highly educated people to cities and generated long-lasting trends in the local human capital. Specifically, on average, local economies that experienced a 1-percentage point larger shock during the 1940s showed a 9-percentage point greater relative growth of college educated workers during 1940–2010. This implies that the clustering of skilled workers leads to the increased relative demand for skilled workers in the long run (Acemoglu, 1998, 2002). The long run change in industrial structures in cities because of the historical WWII shock confirms the hypothesis, in general.

One may think that the estimated effects may be driven by other shocks during this period. For instance, as WWII veterans had other benefits, such as generous home loans or vocational training, the relative skill growth of WWII veterans may be correlated with changes in veteran-dominant occupations or home owners. Moreover, during this period, there was a considerable increase in the labor force participation of women (Acemoglu et al., 2004; Goldin and Olivetti, 2013; Rose, 2018). However, my results on the consequences of the historical shock are highly robust after controlling for these shocks, as well as labor demand shifts driven by the local industrial structure, the indicator for rural areas, and the presence of land-grant universities.

My work relies on recent studies that explain the geographic sorting of skilled workers and its consequences. Previous studies have documented the increasing divergence of skills across cities since 1980 (Berry and Glaeser, 2005;

Moretti, 2012; McHenry, 2014; Diamond, 2016). Moreover, this agglomeration of skills coincides with the increase in local skill premiums along with the rapid skill-biased technical change (Acemoglu, 1998, 2002; Beaudry et al., 2010; Giannone, 2017; Baum-Snow et al., 2018). My results suggest that the WWII veteran-driven shock played a significant role in shaping the geography of skilled workers in the second half of twentieth century.

This paper also contributes to the economic impacts of exogenous local shocks. Since the work of Bartik (1991) and Katz and Murphy (1992), researchers (Black et al., 2005; Moretti, 2010; Notowidigdo, 2011) have focused on the consequences of local labor demand shocks. For studies regarding high skilled supply shocks, there are two strands of literature. The first is the extensive literature on human capital externalities in cities, as reviewed by Moretti (2004b). The second is the literature on high skill immigration and innovation in cities or states (Kerr and Lincoln, 2010; Peri et al., 2015). In general, the available evidence suggests that local high skill supply shocks increase local productivity. I analyze the dynamic consequences of a historical skilled supply shock and describe how it evolves over time in the long run.

Finally, my analysis is also closely related to studies, such as those of Davis and Weinstein (2002), Bosker et al. (2007), Miguel and Roland (2011), and Bleakley and Lin (2012), who search for evidence of the path dependence. These studies generally find that economic activity across locations is largely affected by local historical shocks, although the context may matter for whether path dependence can occur or not. My results also test this path dependence of the local human capital as a function of the historical shock in a modern context of the US over relatively shorter time horizons.

The remainder of this paper is organized as follows. Section 2 describes the historical background of WWII and the data. Section 3 introduces the empirical framework and the construction of an instrumental variable. Section 4 presents the short run effects. Section 5 describes the long run consequences of the historical shock. Section 6 provides the conclusion.

2 Historical Background and Data

2.1 Historical Background

Officially titled the Servicemen's Readjustment Act of 1944, the GI Bill was created to help veterans of WWII. It provided unprecedented federal support for educational investments to returning veterans. Any veteran who had served for at least 90 days or had been discharged because of disabilities acquired during service was eligible for stipends covering tuition and living expenses as long as he/she commenced schooling by July 1951. Although the length of benefits varied from one to four years depending on the length of service and age, most veterans were eligible for all four years of benefits.

Following the end of WWII, a flood of returning veterans enrolled in tertiary education as a result of the GI Bill. The total enrollment increased by more than 50% from the prewar (1939) level of 1.3 million to over 2 million in 1946, with further increases through 1949. To put this in perspective, approximately one in eight returning veterans received college education under the GI Bill.[1]

This large enrollment made WWII veterans a relatively highly educated group. Figure 1 shows the share of college educated individuals by year of birth for three groups of people: WWII veterans, nonveteran men, and women. Across all birth cohorts, the likelihood of being college educated for WWII veterans is higher than that of nonveteran men or women. While the difference among groups does not directly reflect the causal effect of the GI Bill because of the selection into military service, Bound and Turner (2002) and Stanley (2003) estimate that the benefits generated substantial gains in college attainment among WWII veterans.

Certainly, this large number of highly educated returning veterans is likely to affect local labor markets. For example, the rapid increase in college educated veterans may affect the location decisions of nonveterans. To measure the local human capital shock from these returning veterans, I focus on the

[1] See Olson (1973) and Bound and Turner (2002).

period between 1940 and 1950. Figure 2 describes two reasons why this period is appropriate for measuring the historical shock. First, it captures the greatest usage of GI Bill benefits for college education because eligible veterans were required to use these benefits by July 1951. Second, as Korean War (1950–1953) veterans were also eligible for educational benefits, extending the period to 1960 could confound the effects from WWII veterans.

It is noteworthy that the GI Bill also provided other benefits, such as mortgage subsidies and vocational training, to the veterans. This means that the return of WWII veterans possibly captures the effect of these benefits. For example, Fetter (2013) finds a positive association between nonveterans' home ownership and the share of veterans in states. Furthermore, the majority of veterans who purchased homes between 1946 and 1950 were located in suburban areas (Bennett, 1996; Boustan and Shertzer, 2013). To assuage this concern, I include the change in home owners and veteran-intensive occupations in cities as controls in the robustness checks. I will discuss this in detail in Section 4.

2.2 Data: Geography of WWII Veterans

I use the Integrated Public Use Microdata Series version of Census Public Use Microdata Samples from various years (Ruggles et al., 2015). From these samples, I construct the local labor market-level variables, such as my measure of the local human capital shock, and the change in relative supply of nonveteran and female workers.[2] The samples are restricted to the employed population aged 18 to 55 who are not in group quarters. I also restrict the samples to people who are not attending school in order to remove the direct effects from the presence of colleges.

The geographic units of analysis for the period between 1940 and 1950 are state economic areas (SEAs). SEAs are generally either single counties or groups of contiguous counties within the same state. They are defined as

[2] Specifically, the full counts of the 1930 and 1940 samples, 1950 1% sample, 1960 5% sample, 1970 1% Form 2 Metro sample, 1980 5% State sample, 1990 5% State sample, 2000 5% sample, and the American Community Survey 2009–2011 3-Year sample are used.

having similar economic characteristics in 1950 and cover the entire US. The concept is comparable to commuting zones (CZs), which are widely used to analyze local effects in the modern context. I identify 467 SEAs to analyze the impact of the local human capital shock on the relative growth rate of high skilled workers and other outcomes during 1940–1950. For the long run consequences (after 1960) of the shock, I follow 238 CZs, which are consistently identified across different census samples.[3].

The main measure of the GI Bill-driven local human capital shock is the relative growth rate of college educated WWII veterans between 1940 and 1950. Specifically, the post-WWII shock for a local labor market c is calculated as

$$shock_c = \left(\frac{V^H_{c,1950}}{P^H_{c,1940}} - \frac{V_{c,1950}}{P_{c,1940}} \right) = \left(\frac{\Delta V^H_c}{P^H_{c,1940}} - \frac{\Delta V_c}{P_{c,1940}} \right), \tag{2.1}$$

where $P_{c,1940}$ ($P^H_{c,1940}$) is the total (high skilled) population aged 18 to 55 in the prewar period of 1940. People with some years of college education or higher are defined as high skilled.[4] $V_{c,1950}$ ($V^H_{c,1950}$) is the number of (college educated) WWII veterans in 1950. As no one was a WWII veteran in 1940, the term $V_{c,1950}$ is equal to the change in WWII veterans between 1940 and 1950 (ΔV_c). This form is first used by Card and DiNardo (2000) to examine whether immigrant inflows change the distribution of skills across cities. Similarly, using this measure, I analyze the extent to which the returning veterans change the distribution of the human capital across local areas in the short run. I also examine how persistent the shock is in the long run.

The geographic distribution of this shock across cities is highly uneven. Figure 3 visualizes the variation in post-WWII shock across SEAs in the US. Darker colors indicate larger shocks. At first glance, there is considerable variation across local areas. For example, while the mean of the shock across

[3] I use the crosswalks of Autor and Dorn (2013) and Rose (2018). They are available in the author's websites.

[4] Throughout the paper, I interchangeably use the terms "high skilled" and "college educated". The results from an alternative definition that defines people with a bachelor's degree as high skilled are robust.

cities is about 7 percent, some places experienced more than 40 percent of skill increase. Moreover, some areas experienced negative growth in the local human capital.

Table 1 further describes the significant geographic variation by displaying the top 10 and bottom 10 CZs according to the size of the shock. Although the CZs in California occupy most spots in the top 10 lists, other states, such as Georgia and Texas, are also found. A comparison of the top 10 and bottom 10 lists shows that the places with the largest shocks are usually well-known big cities with favorable local conditions. For example, San Jose, which is the area of Silicon Valley, is ranked as 6 in the top 10 list. This may suggest that the size of the shock is determined by other local characteristics. To address this concern, I develop an instrumental variable, which I will discuss in detail in the next section.

3 Empirical Identification

3.1 Basic Framework

The main goal of this paper is to analyze the extent to which returning WWII veterans affect the spatial distribution of nonveterans by skill groups. By examining this extent, I estimate the *overall* growth of the local human capital as a result of the influx of WWII veterans. To see this more clearly, I decompose the changes in relative growth rate into a component determined by the returning veterans and a component determined by changes in the nonveteran population. First, the total local population (P_c) is the sum of the two groups, WWII veterans (V_c) and nonveterans (N_c). With the use of this fact, the relative growth rate of high skilled is

$$\left(\frac{\Delta P_c^H}{P_{c,1940}^H} - \frac{\Delta P_c}{P_{c,1940}}\right) = \left(\frac{\Delta V_c^H}{P_{c,1940}^H} - \frac{\Delta V_c}{P_{c,1940}}\right) + \left(\frac{\Delta N_c^H}{P_{c,1940}^H} - \frac{\Delta N_c}{P_{c,1940}}\right). \quad (3.1)$$

The first term in Equation (3.1) is the relative growth rate of the college educated veterans, my measure of the local human capital shock introduced in Section 2. The second term is the corresponding part for nonveterans. My research question is how much the first term affects the second term and thus the overall growth of the local human capital. Therefore, the basic specification I estimate takes the following form

$$\left(\frac{\Delta N_c^H}{P_{c,1940}^H} - \frac{\Delta N_c}{P_{c,1940}}\right) = \alpha_s + \beta\left(\frac{\Delta V_c^H}{P_{c,1940}^H} - \frac{\Delta V_c}{P_{c,1940}}\right) + \gamma X_c + \varepsilon_c. \tag{3.2}$$

The term α_s captures state fixed effects. The term X_c is a vector of other city-specific controls, and ε_c is a zero-mean idiosyncratic random error. Equation (3.2) implies that the overall growth of the local human capital can be expressed as a function of the relative growth rate of the college educated veterans.

$$\left(\frac{\Delta P_c^H}{P_{c,1940}^H} - \frac{\Delta P_c}{P_{c,1940}}\right) = \alpha_s + (1+\beta)\left(\frac{\Delta V_c^H}{P_{c,1940}^H} - \frac{\Delta V_c}{P_{c,1940}}\right) + \gamma X_c + \varepsilon_c. \tag{3.3}$$

The coefficient β is of my interest. If $\beta > 0$, places with relatively more inflows of skilled veterans have also experienced an increase of skill in nonveterans. If $\beta = 0$, the mobility of nonveterans across the skill groups is not differentially affected by returning veterans across skill groups. Finally, if β is equal to -1, the returning veterans had no overall effect on the local human capital, as their relative growth rate was completely offset by nonveterans. As nonveterans consist of two heterogeneous groups (nonveteran men and women), I separately estimate β for men and women.[5]

Although using the first differenced specification removes fixed city characteristics, the shock could still be correlated with other contemporaneous shocks. To control for important city-level determinants of the local human capital, I first include an indicator for the presence of land-grant universities

[5] Although WWII veterans include a small number of females in reality, all WWII veterans in the 1950 Census are males.

as a control. Land-grant universities were established by the federal Morrill Act of 1862 and have been known to be a strong predictor of the local stock of human capital.[6] Second, the indicator variable for rural areas is also included to control for different trends between rural and urban areas. Finally, I also control for labor demand shifts by using the well-known Bartik index (Bartik, 1991). Specifically, I predict the employment growth of college and non-college educated workers based on each city's industrial structure in 1930.

$$Bartik_c^j = \sum_s \eta_{sc} \Delta E_s^j, \tag{3.4}$$

where η_{sc} denotes the share of total employment in industry s in city c in 1930; ΔE_s^j is the national-level change in the log of employment in the same industry between 1940 and 1950 by workers belonging to skill group j.

While I control for these important controls and state fixed effects, interpreting these estimates as causal requires that the post-WWII shock, the relative growth rate of WWII veterans, be exogenous to other shocks. Because of the postwar migration of veterans, this condition may not be satisfied. Following the war, the veterans had to choose where to attend colleges and universities and, finally, where to work. Therefore, the locations of WWII veterans in 1950 may reflect local economic characteristics. Moreover, it is also possible that the veterans are affected by other groups, such as nonveteran men or women. To deal with these issues, in the next subsection, I introduce an instrumental variable for the post-WWII shock and examine the power and validity of the instrument.

3.2 Instrumental Variable: Power and Validity

To develop an instrument for the WWII vetean-driven local human capital shock, I turn to two previous studies that are relevant for the location choices of veterans. First, Costa et al. (2018) finds that Civil War veterans are more likely

[6] The indicator for land-grant universities has been widely used as an instrument for the local human capital, as it is evenly distributed across the US, and labor markets with and without land-grant universities are not significantly different from one another in terms of human capital when they have been established.

to move to a county where their fellow veterans live, and, as a result, there is geographic clustering in some localities. Second, Campante and Yanagizawa-Drott (2015) document that a father's war service experience has a positive and significant effect on his son's likelihood of wartime service.

These two findings suggest that the past distribution of veterans for the prewar period may predict the locations of WWII veterans after the war. Specifically, because of the strong tendency for veterans to choose locations with existing concentrations of other veterans, there were veteran communities before WWII. This veteran community could play a crucial role in the location choices of WWII veterans. Furthermore, if WWII veterans who were the sons of WWI veterans have preferences for their hometowns, this channel will also predict the return of WWII veterans.

Figure 4 strongly supports this hypothesis by plotting the population share of WWII veterans in 1950 against the population share of any veterans in 1930 across SEAs in the US. First, in 1930, there is a considerable variation in the population share of veterans across areas in the US. The mean population share is about 5.5 percent, but the share ranges between 2.5 and 11.5 percent. Second, this clustering of veterans in 1930 significantly predicts the spatial distribution of WWII veterans. A 1-percentage point increase in the population share of veterans in 1930 is associated with a 0.95-percentage point increase in the population share of WWII veterans in 1950, and this is statistically significant at one percent.

Using this fact, I formally construct the instrument to predict the size of the shock in the following way. First, I predict the number of WWII veterans by skill (V_c^j) from the distribution of veterans in 1930.

$$\widehat{V_c^j} = V_{c,1930} \cdot \left(\frac{V_{1950}^{-s(c)}}{V_{1930}^{-s(c)}} \right) \cdot \tau_j^{-s(c)}, \tag{3.5}$$

where $V_{c,1930}$ is the number of any veterans in area c in 1930, $(V_{1950}^{-s(c)}/V_{1930}^{-s(c)})$ is the national growth of veterans between 1930 and 1950 outside of state s where the local labor market c belongs to, and $\tau_j^{-s(c)}$ is the corresponding fraction of the skill group j among the WWII veterans.

Combining each part from these result in the following final instrument for the WWII veteran-driven local human capital shock:

$$\widehat{shock_c} = \left(\frac{\widehat{V^H_{c,1950}}}{s^H \cdot P_{c,1930}} - \frac{\widehat{V^H_{c,1950}} + \widehat{V^L_{c,1950}}}{P_{c,1930}} \right), \tag{3.6}$$

which has much analogy with the $shock_c$ in Equaltion (2.1). In standardizing the predicted values, I use the population in 1930 (instead of the population in 1940). For college educated population, I simply multiply the mean fraction of college educated people in 1940 (s^H) to the population in 1930 ($P_{c,1930}$).

Table 2 shows the rankings of CZs according to the size of this predicted shock, instead of the rankings based on the size of the actual shock in Table 1. Notably, the lists of CZs in the top 10 and bottom 10 are very different in Table 2, whereas the size of the predicted shock is reasonably correlated with the size of the actual shock. In addition, in the top 10 list of Table 2, we see a greater number of small CZs, such as Newport News, which relieves the concern that the size of the actual shock could be correlated with other local characteristics.

Table 3 formally presents the first-stage regression results from this instrument. Regressions are weighted by the total population in 1940. Standard errors are clustered at the state level. Column 1 shows the results with state dummies only. The estimated coefficient and F-statistics imply that the results are reasonably strong. The coefficient is approximately 0.9, meaning that a 1-percentage point increase in the predicted number of college educated WWII veterans leads to an actual increase of 0.9-percentage point. In addition, the F-statistics of 29 are strong enough to avoid the small sample bias of a weak instrument. The same conclusion applies to column 2, where I add Bartik shocks, the presence of land-grant universities, and the dummy for rural areas. In Column 3, I additionally control for local characteristics (as of 1930), including the share of nonwhites, immigrants, and those aged 18 to 40. Even after controlling for these characteristics, the instrument retains its power. In Column 4, I use the population share of veterans in 1930 as an instrumental variable. Finally, Column 5 runs exactly the same specification as in Column

2 using CZs. It shows similar effects, although the power is a bit weaker as the number of observations decreases to 238 from 467.

One may think that this instrument essentially uses the same variation in the military mobilization for WWII, which was used as an instrument for female labor supply in Acemoglu et al. (2004). This is because the mobilization rates likely predict the locations of WWII veterans in 1950 if the veterans went back to where they were drafted. To test this hypothesis and whether my instrument exploits the same variation, in Table A1 in the Appendix, I regress the distribution of WWII veterans in 1950 on my instrument and the mobilization rates.[7] The results suggest that my instrument strongly predicts the location of WWII veterans even after controlling for the mobilization rates and other covariates. This relieves the concern that the prewar veteran community exploits the same variation.

Recall that the use of this instrument hinges on an important assumption: the historical differences in share of veterans—after controlling for other city characteristics and shocks—affected the change in college educated people only through college educated WWII veterans. That is, it is exogenous to other confounding shocks, such as local demand shifts, affecting the growth of the local human capital.

While the distribution of veterans in 1930 is not purely random, it is at least predetermined and likely to satisfy this assumption for the following reasons. First, WWI veterans, who are the majority of veterans in 1930, did not have educational benefits similar to those provided by the GI Bill. Hence, their distribution is unlikely to be correlated with the trends in local skills. This would also lower the likelihood of endogenous migration in the pursuit of higher education, and, therefore, their distribution is less likely to be correlated with unobservable persistent local factors. Second, although the exclusion restriction is not testable, the instrument is not significantly correlated with the pre-trends of my outcome variables.

Figure 5 describes the long run trends of college educated population for high and low veteran share areas. Until 1940, the two trends are fairly parallel

[7] As the mobilization rates vary by states, the regressions are done at the state-level.

to each other, while high veteran share areas in general show higher level of high skilled workers.[8] Following the war in 1950, however, the two trends begin to diverge. Because of the inflow of highly educated WWII veterans, high veteran share areas experienced an increase in high skilled. On the other hand, college educated population in low veteran share areas slightly decreased. Then, the increased gap between the high and low veteran share is lasting over time. This preliminary result suggests the persistent effects from the veteran-driven human capital shock.

Figure 6 directly plots the pre-period (1935–1940) changes of the outcome variables (male and female) against the population share of veterans in 1930. Notably, the two pre-trends show essentially no correlations with the veteran shares in 1930. This explains that high and low veteran share areas could have trended similarly after 1940, without the veteran-driven shock. Thus, if there are any significant changes in local skill during the main period (1940–1950), these effects are likely from the return of WWII veterans.

Table 4 formally presents the results from these falsification tests. To be specific, I regress the pre-trends of my outcome variables on the instrument ($\widehat{shock_c}$) in Equation (3.6). The first two columns examine the pre-trends (1935–1940) of the growth in local skill from the migration for men and women, respectively. As expected, the estimates are fairly close to zero. The last three columns further examine the correlation between the instrument and other outcome variables (change in population, employment, and manufacturing employment for 1930–40). Reassuringly, they are not significantly correlated with the instrument, and they provide suggestive evidence that the instrument likely satisfies the identifying assumption.

Overall, the first-stage regressions and falsification tests demonstrate that the instrument—based on the historical share of veterans in 1930—strongly

[8] Since the information on educational attainment is not available in the 1930 Census, I estimate the value in 1930 using the occupational structure of each area in 1930. Specifically, I multiply the number each occupation (3-digit) for each area in 1930 with the share of college educated for each occupation in 1940. Then, I sum across the occupations for each area. The value in 1935 is calculated using the information on migration status in the 1940 Census.

predicts the actual local human capital shock after the war and is not correlated with unobservable confounding shocks.

4 Short run: 1940–1950

4.1 A Reshuffle of the Local Human Capital

The flood of highly educated returning veterans may have an indirect impact on the local stock of other college educated people in cities. It is easy to imagine that these returning veterans crowd out nonveterans and females if they are closer substitutes. This is crucial to the short run effect because the *overall* increase in the local human capital would be zero if the veteran-driven human capital shock were to be completely offset by nonveteran men or women in local areas.

As discussed above, the sign of β in Equation (3.2) depends on the degree of complementarity between WWII veterans and nonveterans. If their jobs and tasks are significantly different and complementary, then the return of highly educated veterans will result in an increase in other skilled people. On the other hand, if WWII veterans and nonveterans are competing for the same jobs, the increase in local skill from veterans would be offset by the out-migration of other educated workers.

For these reasons, before presenting the estimation results, I provide a distribution of WWII veterans in comparison to other groups (nonveteran men and women) across broadly defined occupations. Table 5 shows the distribution of these three groups: WWII veterans, nonveteran men, and women. Panel A presents the distribution for all people, whereas Panel B shows only that for college educated people. The first impression is that the occupational distribution of WWII veterans is quite different from that of women. Relative to women, WWII veterans are highly concentrated in craftsmen jobs and are less employed in clerical and kindred jobs. Even within the college educated group, the veterans are relatively evenly distributed, but for women, more than 80 percent are professional or clerical jobs. Second, veteran and nonveteran men work in relatively similar jobs, whereas there are still notable differences in occupations, such as farmers. Therefore, these results imply that the veteran-driven shock possibly increases the local skill of women because of the complementarity involved, but it decreases the skill of or has no effect on nonveteran men.

Table 6 explains the estimation results. Regressions are weighted by the local population in 1940. Standard errors are clustered by states. Each panel indicates the outcome variables of the regressions. The first two columns show the estimates from the OLS regressions. Column 1 shows the SEA-level regression with the Bartik index, the dummy for land-grant universities, and the dummy for rural areas. Column 2 runs the same regression for CZs. The results from these OLS regressions explain that the shock significantly increased the local skill of women, whereas had no effect on nonveteran men. Specifically, the shock is associated with a 0.11 to 0.18-percentage point increase in the skill of nonveteran women, resulting in an overall 1.1 to 1.25-percentage point increase in the local human capital. However, as discussed before, these correlations may be spurious, as there are other shocks that may affect the shock and the outcome variables in the same way.

To examine this possibility, I run 2SLS regressions using my instrument in Columns 3 thorough 6 Table 6. Column 3 is my baseline specification that controls for the Bartik index, the indicator for the presence of land-grant universities, and the dummy for rural areas. Column 4 further controls for local characteristics, including share of nonwhites, immigrants, and those aged 18 to 40 (all as of 1930). Column 5 uses the simple veteran shares in 1930 as an instrument. Finally, Column 6 examines the baseline specificaiton by using CZs, which will be used for the long run analysis.

Interestingly, there are differences for nonveteran men (Panel A) and women (Panel B). The 2SLS estimates on nonveteran men become negative, and these negative effects are sometimes significant. On the other hand, for women, the 2SLS estimates are positive and slightly larger than the OLS estimates, although they are not statistically significant. In other words, the shock has decreased the local skill of nonveteran men, whereas it has had positive or no effect on the skill composition of women. This result implies that skilled women were complements, whereas nonveteran men were substitutes for college educated veterans. This interpretation is in line with Table 5, which documents complementary occupational distributions between WWII veterans and women, as well as similar distributions between veteran and nonveteran men.

For the small positive effects on women, there is another channel that can explain the increase in skill composition of women as a result of the historical shock. If college educated men tend to marry college educated women, this would also contribute to the increase in the relative skill of women (Costa and Kahn, 2000). In this sense, Larsen et al. (2015) find that WWII veterans married women with higher education. This would additionally affect the geographic sorting of educated workers during this period. According to the 1960 Census, about 43.5 percent of college educated WWII veterans married college educated women.[9] These figures should be reflected in the estimates for women.

One might think that the positive effect on women is contradicting the previous literature on the effect of WWII mobilization on women's educational attainment. Jaworski (2014) documents that the manpower mobilization for WWII lowered the educational attainment of women during the early 1940s. However, the effect I examine is slightly different from that of Jaworski (2014). I investigate whether the *presence* of educated WWII veterans affects other people's location choices, whereas Jaworski (2014) answers how exposure to manpower *mobilization* affects women's education.[10]

Overall, the post-WWII shock significantly reshapes the geographic distribution of human capital during 1940–1950, because the veteran-driven shock is not completely offset by others. Specifically, a 1-percentage point larger shock (approximately a 12 percent increase in the relative growth rate of college ed-

[9] In the 1950 Census, educational attainment is one of the sample-line variables so that only the educational attainment information of one person per household is available.

[10] There are also minor differences. First, the crowd-out effects of mobilization are mostly on high school education, not college education. Second, Jaworski (2014) examines the effects within the same year of birth, whereas my effects are based on broader groups, those aged 18 to 55.

ucated WWII veterans) leads to a 0.86 to 1.2-percentage point increase (a 6 to 9 percent increase) in the local human capital. In subsection 5, I examine how this short run increase affects the local human capital in the long run (1960–2000). The positive effects of the veteran-driven shock on the growth of local skill are comparable to that in the literature on the mobility effects of supply shock with a similar empirical design. For instance, Card and DiNardo (2000) find that an increase in the immigrant population in specific skill groups leads to a small increase in the native-born population in the same skill group.

4.2 Robustness Checks

As discussed in Section 3.2, in estimating the causal effects of the post-WWII shock, the shock ($shock_c$) should be exogenous to other local shocks. In other words, the location choices of WWII veterans must be exogenous to demand shocks and other unobservable determinants of the local human capital. In this subsection, to tackle several threats to this identification assumption, I examine the robustness of my results by controlling for other potential shocks that might have affected the local human capital during the period of 1940–1950.

There are two potential threats that might bias my estimates. First, as documented by Acemoglu et al. (2004), there was a signficant increase in female labor supply because of the mobilization for WWII during 1940–1950. Although I have shown that the variation I use is not the same as the WWII mobilization rates, a correlation between my instrument and the change in labor supply of women might confound the estimates. Second, as discussed in Section 2, WWII veterans had other benefits to use, including benefits for vocational training and generous home loans. Therefore, the estimated results could mix the effects from the increase in veteran-intensive occupations or home owners in local economies.

As directly controlling for these shocks may introduce endogeneity (i.e., these shocks could be the results of the veteran-driven local human capital shock), I predict each shock (the change in female employment, veteran-intensive occupations, and home owners) from the predetermined distribution of each corresponding group. The detailed procedure for the construction of these variables is shown in the Appendix. Then, I include them as control variables and see if the estimates are robust across different specifications.

Table 7 shows the results from the robustness checks. Column 1 includes the change in female workers as a control. Column 2 controls for the change in veteran-intensive jobs, which captures the use of vocational training benefits. Column 3 controls for the change in male home owners. Finally, in Column 4, I also drop SEAs in the West regions because these areas in general experienced larger shocks. Across the four columns, the results are highly robust. In particular, the effects on nonveteran men are always negative and significant, but the effects on women are positive and insignificant. As a result, the overall effects on local skill are slightly smaller than 1, but not statistically different from 1. This suggests that the historical shock significantly reshuffles the spatial distribution of skill even after controlling for various other local shocks.

Overall, the results from this subsection suggest that my results indicating that the historical shock strongly reshaped the distribution of human capital during the 1940s are not sensitive and robust across different specifications.

5 Long Run: After 1960

The results from the previous section indicate that the WWII veteran-driven shock significantly increased the local human capital across the US during 1940–1950. In this section, I examine whether this short run increase had persistent effects on the local human capital in the long run for the period between 1940 and 2010. For the same period, I also track the effects of the shock on the local industrial structure to investigate the possible mechanisms of the persistence in the local human capital.

For the long run analysis of the local human capital, the dependent variable is similar to the left-hand side variable, the relative growth rate of high skilled, in Equation (3.3). However, the growth rate is measured for the relevant long run period instead of the 1940s. Furthermore, the relative growth rate is divided by the number of decades for the corresponding period. Of particular interest are the effects after 1980. As I restrict my sample to adults aged 18 to 55 in each census year, no WWII veterans were counted in the dependent variable after 1987. Therefore, if such effects are positive and significant, it means that the effects are intergenerational in the sense that new generations of skilled workforce are located in cities that have had a larger human capital shock in the past.

Before presenting the regression results, I examine the simple correlations between the veteran shares in 1930 and the relative growth rate of high skilled in the short and long runs. Figure 7 presents these correlations. The left figure shows a significant positive correlation between the veteran shares in 1930 and the relative growth in the short run (1940–1950), as documented in the previous section. The right figure plots the same scatter plot for the long run period (1940–2010). Interestingly, although there is more variation in the long run growth of local skill, the long run growth is still positively correlated with the veteran shares in 1930.

Table 8 formally presents the effects of the shock on the local human capital in the long run. The units of observations are CZs. First, the estimates for the short run (1940–1950) are comparable to those in Table 6. That is, a 1-percentage point larger shock leads to a 0.88 (0.28)-percentage point greater skill growth of men (women) and a 1.17-percentage point increase in the overall skill. Note that here, I include WWII veterans under men, so the estimate for men is not significantly different from 1. This short run increase had persistent effects on the local human capital. The effects of the shock gradually increase until 2000, resulting in a 10-percentage point larger the relative growth rate on average. Although the average effects began to decrease after 2000, the impacts are highly significant even in 2010, with growth of a 9-percentage point. For the effects on men and women, they were slightly larger for men, but in 2010 the effects are almost comparable. Overall, these results indicate that having educated people in local areas attracts other skilled people over time, making a virtuous cycle of the local human capital.

These long lasting effects from the historical shock on the local human capital are consistent with previous findings that areas with highly educated people cluster geographically. For example, Moretti (2012) argues that cities with the *right* industries and skilled workers attract more of the same. More specifically, Berry and Glaeser (2005) state that skilled entrepreneurs and managers disproportionately hire skilled labor. My results causally confirm this story by documenting the two facts. First, in the previous section, I have shown that the historical shock significantly reshaped the distribution of human capital in 1950. Second, over time, cities that had a larger shock experienced significant growth in the local human capital. Previous studies (Berry and Glaeser, 2005; Diamond, 2016) have shown that shifts in the local labor demand toward skilled people is the fundamental cause of the skill sorting.

To test this mechanism, I examine the change in local industrial structure, induced by the historical human capital shock. I track two large sectors (manufacturing and service) by skill.[11] The dependent variable is the change in the number of workers in the sectors as a share of the local population in 1940. Table 9 presents the results. While high skilled industries both in manufacturing and service expanded because of the historical shock, the trends are clearly different between the two sectors. High skilled manufacturing sectors have grown most significantly during 1940–1970 as a result of the shock, but the effects gradually decreased after 1970. On the other hand, high skilled service sectors expanded gradually over time because of the shock, and the largest effects were found after 1980. For the low skilled sectors, the employment in the service sectors increased significantly as a result of the shock. The mechanism for this large increase in low skilled service is likely driven by spillovers from high skill consumption, as documented by Moretti (2010) and Mazzolari and Ragusa (2013).

[11] A sector is defined as high skilled manufacturing (service) if the share of high skilled workers in the sector is higher than or equal to the upper 25th percentile of the distribution of the share of high skilled workers across manufacturing (service) sectors in 1940.

6 Conclusion

This paper discusses the importance of a local human capital shock in the subsequent formation of the local human capital by using a plausibly exogenous variation in WWII veteran-driven relative growth of skilled labor force. This first local human capital shock in modern US history greatly reshaped the spatial distribution of skills after WWII. Furthermore, this shock generated long lasting trends in the local human capital. Specifically, cities that had a 1-percentage point larger shock after WWII experienced a 6.3-percentage point increase in skill during 1940–2010. The changes in local industrial structures in favor of skilled jobs explain that shifts in the local labor demand toward skilled workers is the cause of the skill sorting.

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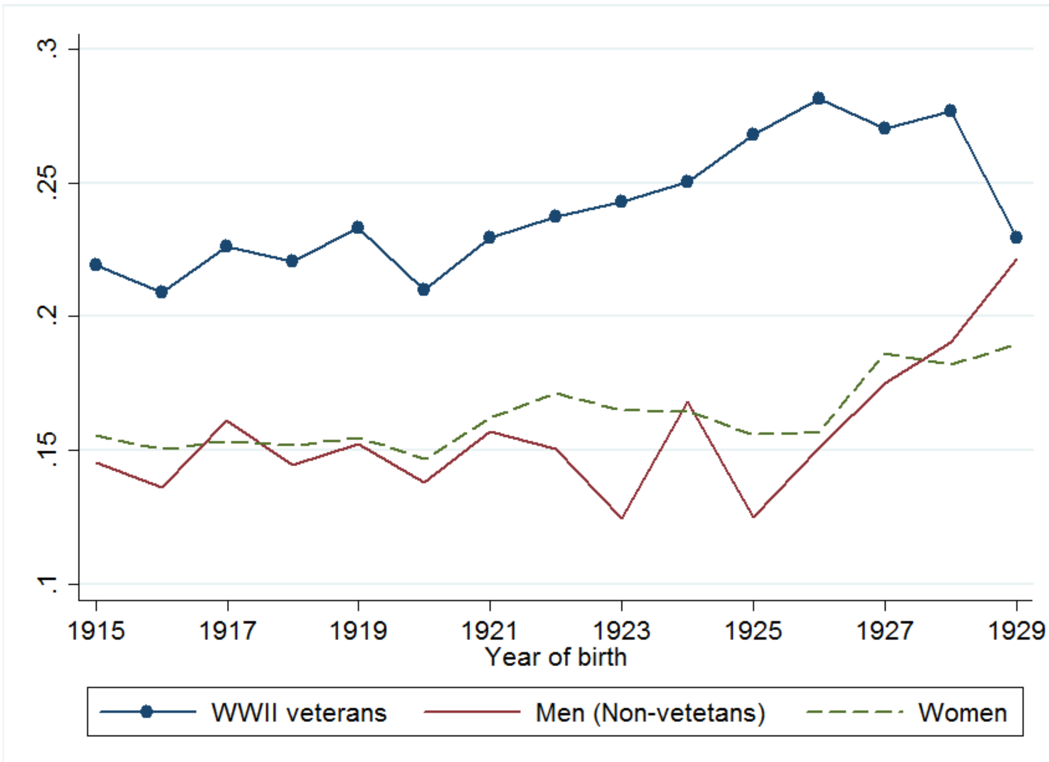
Figures and Tables

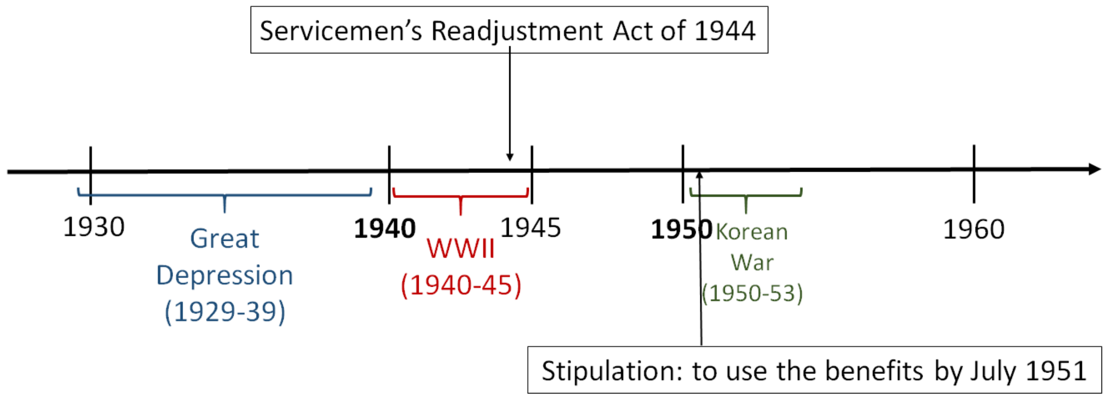
Figures

Figure 1: Share of college educated by year of birth in 1950



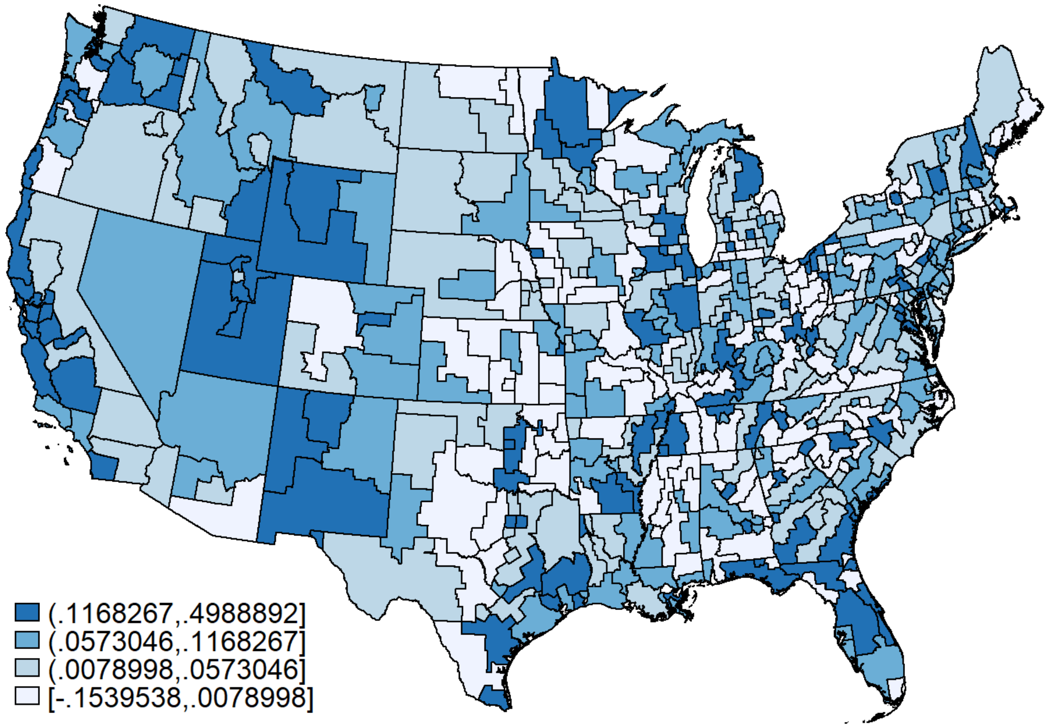
Note: Author's calculations from IPUMS (Ruggles et al. 2015) version of the Decennial Census 1950 1% sample. People with some years of college education or higher are counted as college educated.

Figure 2: Timeline around the World War II



Note: Historical timeline around the WWII. The main period for measuring the local human capital shock is 1940–1950.

Figure 3: The geography of the post-WWII local human capital shock

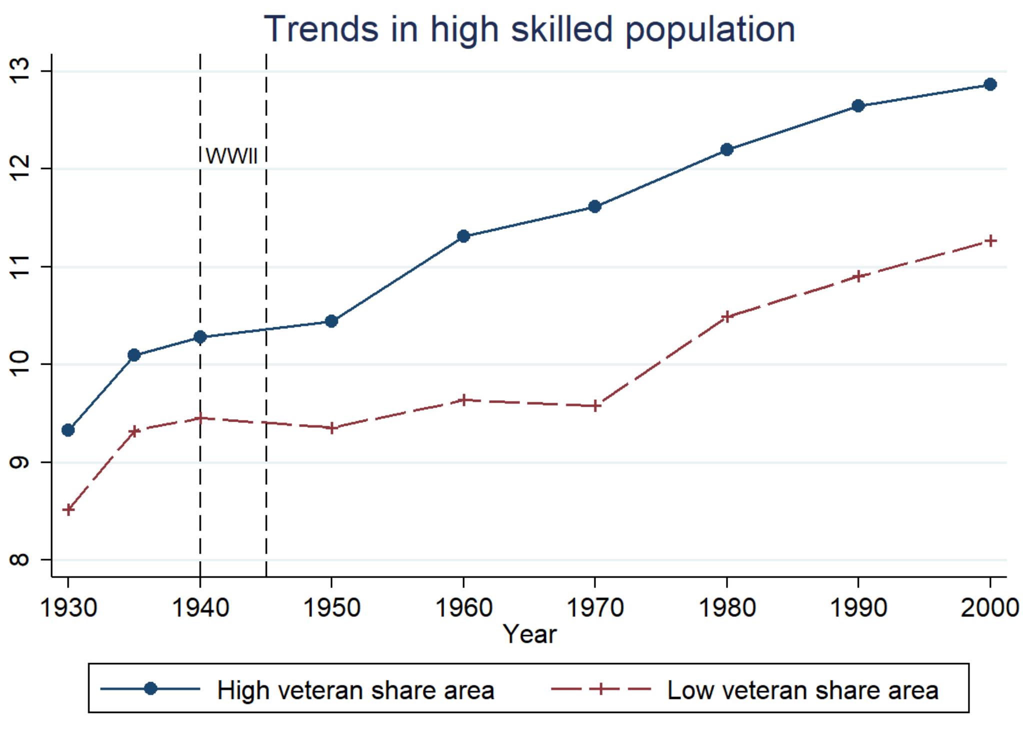


Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1940 full-count and 1950 1% sample. The post-WW2 shock is defined as the relative growth rate of college educated WW2 veterans. The units of observations are SEAs. People with some years of college education or higher are counted as college educated. The relative growth rate is based on employed people aged 18 to 55 in each SEA. The number of observations is 467.

Figure 4: Correlation between population share of veterans in 1930 and in 1950

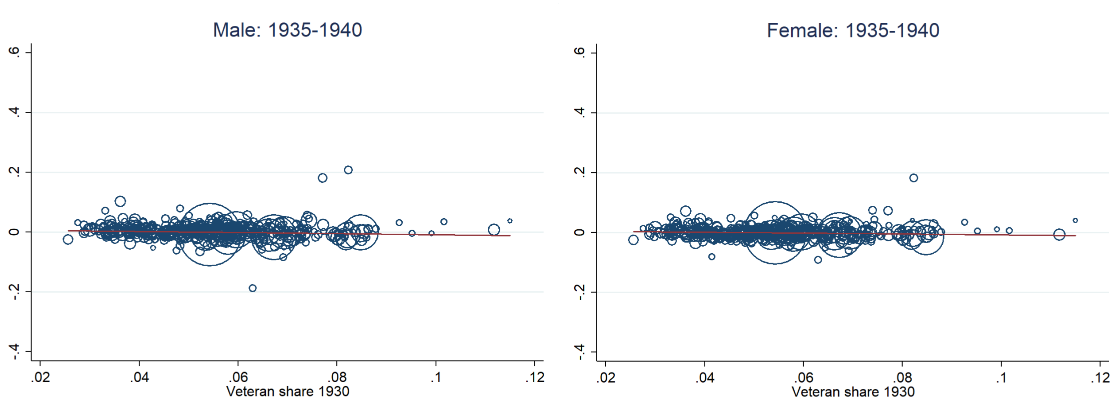
Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1930 full-count and 1950 1% sample. The size of circle represents the local population in 1930. The linear regression fit is weighted by the local population in 1930. The units of observations are SEAs. The number of observations is 467.

Figure 5: Comparison between high and low veterans share areas



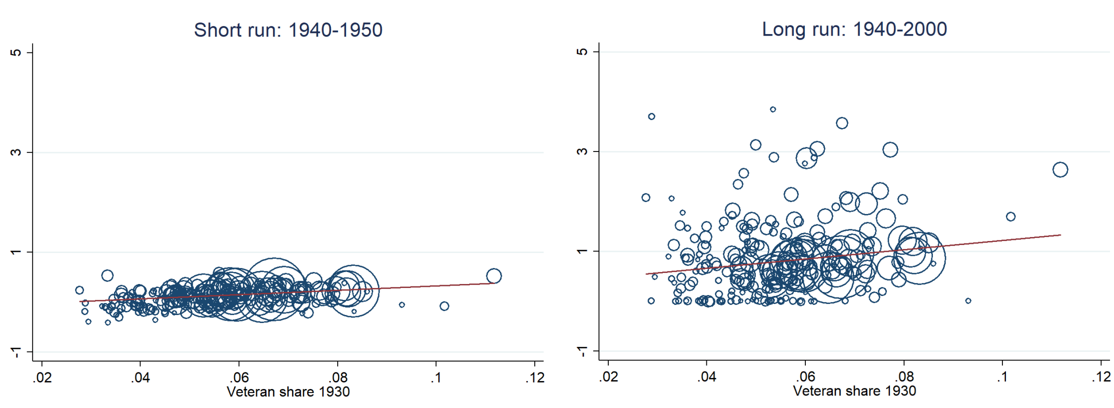
Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Censuses. The values in 1930 are estimated using information on occupations. The units of observations are SEAs (CZs) for 1930-1950 (1960-2000).

Figure 6: Pre-trends and veteran share 1930



Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1940 full-count sample. The size of circle represents the local population in 1940. The linear regression fit is weighted by the local population in 1940. The units of observations are SEAs.

Figure 7: The post-WW2 shock and relative skill growth



Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1940 full-count, 1950 1% sample, and ACS 3-year sample of 2009-2011. The size of circle represents the local population in 1940. The linear regression fit is weighted by the local population in 1940. The units of observations are CZs. The number of observations is 294.

Tables

Table 1: Top 10 and Bottom 10 CZs of the post-WW2 shock

Top 10			
	Commuting Zone	State	Shock
1	Columbus	GA	0.367
2	San Diego	CA	0.263
3	Savannah	GA	0.249
4	Atlanta	GA	0.241
5	Santa Barbara	CA	0.239
6	San Jose	CA	0.225
7	Sacramento	CA	0.221
8	Corsicana	TX	0.212
9	Carbondale	IL	0.206
10	Santa Rosa	CA	0.204

Bottom 10			
	Commuting Zone	State	Shock
1	Roseburg	NY	-0.133
2	Columbus	IN	-0.129
3	Wichita	KA	-0.105
4	Chickasha	OK	-0.097
5	Brownwood	TX	-0.090
6	Hickory	NC	-0.074
7	Zanesville	OH	-0.070
8	Fargo	ND	-0.068
9	Florence	AL	-0.067
10	Columbia	MO	-0.065

Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1940 full-count and 1950 1% sample. The units of observations are CZs. People with some years of college education or higher are counted as college educated. The samples are based on the employed population aged 18-55 in 1940 for each CZ.

Table 2: Top 10 and Bottom 10 CZs of the *predicted* shock

	Top 10			
	Commuting Zone	State	Actual	Predicted
1	Washington DC	DC	0.184	0.710
2	Bridgeport	CT	0.085	0.572
3	San Diego	CA	0.263	0.533
4	Newport News	VA	0.081	0.506
5	Rock Springs	WY	0.027	0.464
6	Providence	RI	0.018	0.463
7	Newport	OR	0.024	0.429
8	Portland	OR	0.138	0.424
9	Roseburg	OR	-0.133	0.416
10	Minneapolis	MN	0.113	0.410

	Bottom 10			
	Commuting Zone	State	Actual	Predicted
1	Dover	DE	0.058	0.139
2	Dublin	GA	-0.032	0.143
3	LaGrange	GA	0.039	0.144
4	Colonial Beach	VA	-0.034	0.147
5	Thomasville	GA	-0.046	0.161
6	Brownsville	TX	0.171	0.162
7	Goldsboro	NC	-0.003	0.165
8	Barnwell	SC	0.009	0.165
9	New Albany	MS	-0.019	0.168
10	Cookeville	TN	-0.038	0.169

Note: Author's calculations from IPUMS (Ruggles et al. 2015) versions of the Decennial Census 1930 full-count, 1940 full-count, and 1950 1% sample. The units of observations are CZs. People with some years of college education or higher are counted as college educated. The samples are based on the employed population aged 18-40 in 1940 for each CZ.

Table 3: First stage power

	(1) Basic	(2) Baseline (SEA)	(3) Control: 1930 charact.	(4) Using Veteran share	(5) Baseline (CZ)
Predicted shock	0.880***	0.685***	0.685***		0.454***
	(0.163)	(0.182)	(0.200)		(0.132)
Veteran share 1930				2.198***	
				(0.548)	
1st-stage F	29.21	14.12	11.69	16.06	11.91
Geographical Unit	SEA	SEA	CZ	SEA	SEA
Weighted	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	238
R-squared	0.310	0.324	0.359	0.329	0.570

Note: The dependent variable is the relative growth rate of college educated WWII veterans. The explanatory variable is the predicted relative growth rate of college educated WWII veterans. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the population aged 18 to 55 in 1940. Baseline controls include Bartik shocks, the indicator for Land-grant universities, and the indicator for rural areas. People with some years of college education or higher are counted as college educated.

**p< 0.01, **p< 0.05, *p< 0.1

Table 4: Falsification Tests

	(1) Male relative growth (1935–40)	(2) Female relative growth (1935–40)	(3) Population growth (1930–40)	(4) Employment growth (1930–40)	(5) Manufacturing growth (1930–40)
Predicted shock	0.064	0.061	0.670	0.635	0.236
	(0.072)	(0.052)	(0.427)	(0.530)	(0.798)
Weighted	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	467
R-squared	0.211	0.178	0.368	0.402	0.511

Note: The explanatory variable is the predicted relative growth rate of college educated WWII veterans. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the local population aged 18 to 55 in 1940. Baseline controls include Bartik shocks, the indicator for Land-grant universities, and the indicator for rural areas. People with some years of college education or higher are counted as college educated.

***p< 0.01, **p< 0.05, *p< 0.1

Table 5: Distribution of Workers across Occupations, 1950

	WWII veterans	Nonveteran (men)	Nonveteran (women)
Panel A: All skill groups			
Professional and Technical	9	7	11
Managers, Officials, and Proprietors	10	11	4
Clerical and Kindred	8	6	31
Sales workers	8	6	8
Craftsmen	23	20	2
Operatives	23	21	21
Service workers	5	5	19
Farmers	8	16	3
Laborers	7	9	1
Panel B: College educated			
Professional and Technical	33	34	46
Clerical and Kindred	11	8	34
Sales workers	13	10	5
Craftsmen	13	10	1

Notes: Each column shows the percent of workers from the group in various occupation categories in 1950. All numbers are rounded to the nearest integer. For Panel B, only top 4 occupations in the share of college educated are shown.

Table 6: Short run effects

	OLS		2SLS			
	(1) Baseline	(2) Baseline (CZ) charact.	(3) Baseline	(4) Control: 1930 charact.	(5) IV: simple share	(6) Baseline (CZ)
Panel A: Nonveteran men						
Post-WWII shock	-0.010	0.072	-0.336**	-0.265	-0.278*	-0.116
	(0.052)	(0.080)	(0.162)	(0.193)	(0.168)	(0.325)
Panel B: Women						
Post-WWII shock	0.115**	0.181**	0.199	0.147	0.179	0.283
	(0.046)	(0.070)	(0.189)	(0.194)	(0.167)	(0.302)
Panel C: Relative skill growth						
Post-WWII shock	1.105***	1.253***	0.862***	0.882***	0.902***	1.167**
	(0.065)	(0.119)	(0.278)	(0.291)	(0.257)	(0.519)
1st-stage F	-	-	14.12	11.69	16.06	11.91
Geographical Unit	SEA	SEA	SEA	SEA	SEA	CZ
Weighted	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467	238	467	467	467	238

Note: The units of observations are SEAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the local population aged 18 to 55 in 1940. Baseline controls include Bartik shocks, the indicator for Land-grant universities, and the indicator for rural areas. People with some years of college education or higher are counted as college educated.

***p< 0.01, **p< 0.05, *p< 0.1

Table 7: Robustness Checks

	(1) Control: ΔFemale employment	(2) Control: ΔVA-intensive jobs	(3) Control: ΔHome owners	(4) Dropping West regions
Panel A: Nonveteran men				
Post-WWII shock	-0.278*	-0.446**	-0.329*	-0.404**
	(0.167)	(0.213)	(0.180)	(0.162)
Panel B: Women				
Post-WWII	0.172	0.282	0.158	0.213
	(0.203)	(0.242)	(0.199)	(0.215)
Panel C: Relative skill growth				
Post-WWII	0.894***	0.836***	0.829***	0.808***
	(0.285)	(0.306)	(0.303)	(0.301)
1st-stage F	13.04	10.18	11.85	10.96
Weighted	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	467	467	467	400

Note: The units of observations are SEAs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the local population aged 18 to 55 in 1940. People with some years of college education or higher are counted as college educated.

***p< 0.01, **p< 0.05, *p< 0.1

Table 8: Long run effects on local human capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1940–50	1940–60	1940–70	1940–80	1940–90	1940–2000	1940–2010
Panel A: Men							
Post-WWII	0.884***	1.070***	1.983***	3.619***	5.335***	5.227***	4.528***
shock	(0.325)	(0.343)	(0.611)	(1.165)	(1.267)	(1.208)	(1.049)
Panel B: Women							
Post-WWII	0.283	0.347***	1.040***	2.388***	4.603***	4.960***	4.481***
shock	(0.302)	(0.110)	(0.292)	(0.709)	(1.044)	(1.115)	(1.030)
Panel C: Relative skill growth							
Post-WWII	1.167**	1.417***	3.023***	6.007***	9.938***	10.187***	9.009***
shock	(0.519)	(0.442)	(0.897)	(1.871)	(2.308)	(2.318)	(2.074)
1st-stage F	11.91	11.91	11.91	11.91	11.91	11.91	11.91
Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238	238	238	238	238	238	238

Note: The units of observations are CZs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the local population aged 18 to 55 in 1940. People with some years of college education or higher are counted as college educated.

***p< 0.01, **p< 0.05, *p< 0.1

Table 9: Effects by industry

	(1) 1940–50	(2) 1940–60	(3) 1940–70	(4) 1940–80	(5) 1940–90	(6) 1940–2000	(7) 1940–2010
Panel A: Manufacturing (High skilled)							
Post-WWII	0.251**	0.335**	0.357**	0.329**	0.258***	0.180***	0.150**
shock	(0.113)	(0.159)	(0.151)	(0.164)	(0.097)	(0.066)	(0.060)
Panel B: Manufacturing (Low skilled)							
Post-WWII	-0.083	0.126	0.368**	0.187	0.199**	0.145**	0.126***
shock	(0.113)	(0.128)	(0.161)	(0.116)	(0.091)	(0.059)	(0.046)
Panel C: Service (High skilled)							
Post-WWII	0.328***	0.399**	0.672***	0.802***	0.967***	0.998***	0.945***
shock	(0.109)	(0.162)	(0.231)	(0.248)	(0.252)	(0.253)	(0.248)
Panel D: Service (Low skilled)							
Post-WWII	1.345***	1.292***	1.697***	1.837***	2.023***	1.915***	1.645***
shock	(0.363)	(0.429)	(0.546)	(0.557)	(0.553)	(0.518)	(0.467)
1st-stage F	11.91	11.91	11.91	11.91	11.91	11.91	11.91
Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	238	238	238	238	238	238	238

Note: The units of observations are CZs. Standard errors in parenthesis are heteroskedasticity-robust and clustered by state. All the regressions are weighted by the local population aged 18 to 55 in 1940. People with some years of college education or higher are counted as college educated.

***p< 0.01, **p< 0.05, *p< 0.1

Appendix

Veteran Communities and WWII mobilization

Table A1: Locations of WWII veterans in 1950, state-level

	(1)	(2)	(3)	(4)
Veteran Share 1930	1.726***		1.554**	1.244*
	(0.506)		(0.603)	(0.641)
WWII-mobilization		0.372**	0.141	-0.103
		(0.140)	(0.085)	(0.171)
Controls				Yes
Weighted	Yes	Yes	Yes	Yes
Observations	49	47	47	47
R-squared	0.396	0.188	0.426	0.726

Note: The dependent variable is the population share of WWII veterans in 1950. Robust standard errors are in parenthesis. All the regressions are weighted by the local population aged 18 to 55 in 1930. WWII mobilization rates and controls are from Acemoglu et al. (2004).
**p< 0.01, **p< 0.05, *p< 0.1

Construction of other shocks

6.1 The change in female employment

To construct the predicted change in the female employment, I first calculate the imputed number of female employment for SEA c in year t (1940 or 1950) in the following way:

$$\widehat{F_{ct}} = \sum_g F^g_{c,1930} \cdot \frac{F^g_t}{F^g_{1930}}, \tag{A1}$$

where the first term F^g_{1930} is the total female population of SEA c for age group g in 1930 and (F^g_t/F^g_{1930}) is the national growth of the female employment between 1930 and year t for each age group g. The age groups are classified as the following: 18-25, 26-35, 36-45, and 46-55. Then, I take the first difference in these numbers for the period 1940–1950 and divide them by the total female population in 1940 ($P^{female}_{c,1940}$).

6.2 The change in male veteran-dominant occupations

To construct the predicted change in the male veteran-dominant occupations, I first define the veteran-dominant occupations in the following way: a occupation is defined as veteran-dominant if the occupation is belong to the upper 5th percentile of the distribution of the WWII veterans across the occupations in 1950. Then I calculate the imputed number of the veteran-dominant occupations for SEA c in year t (1940 or 1950) in the following way:

$$\widehat{VD^k_{ct}} = \sum_k VD^k_{c,1930} \cdot \frac{VD^k_t}{VD^k_{1930}}, \tag{A2}$$

where the first term $VD_{c,1930}$ is the veteran-dominant employment of sub-occupation k of SEA c in 1930 and (VD^k_t/VD^k_{1930}) is the national growth of sub-occupation k between 1930 and year t. Finally, I take the first difference in these numbers for the period 1940–1950 and divide them by the total male population in 1940 ($P^{male}_{c,1940}$).

6.3 The change in male home owners

To construct the predicted change in male home owners, I first calculate the imputed number of the male home owners for SEA c in year t (1940 or 1950) in the following way:

$$\widehat{O_{ct}} = \sum_g O^g_{c,1930} \cdot \frac{O^g_t}{O^g_{1930}}, \tag{A3}$$

where the first term $O^g_{c,1930}$ is the total male home owners of SEA c for age group g in 1930 and (O^g_t/O^g_{1930}) is the national growth of male home owners between 1930 and year t for each age group g. The age groups are classified as the following: 18-25, 26-35, 36-45, and 46-55. Then, I take the first difference in these numbers for the period 1940–1950 and divide them by the total male population in 1940 ($P^{male}_{c,1940}$).