Why Didn't the U.S. Unemployment Rate Rise at the End of WWII?*

Shigeru Fujita† Valerie Ramey‡ Tal Roded§

March 13, 2026

Abstract

This paper investigates why the U.S. unemployment rate rose only a few percentage points despite the dramatic decline in government spending and other upheaval at the end of World War II. Using a new longitudinal data set based on archival sources and government surveys, we study the many facets of this question. Our findings suggest the following answers. First, the dramatic decline in government spending led to a significantly smaller decrease in GDP than predicted by standard Keynesian models. Instead, private job creation surged as private activity was "crowded in" by the fall in government spending. Second, even accounting for the smaller fall in GDP, the unemployment rate rose much less than predicted by Okun's Law. We develop a new decomposition method that reveals how unusual movements in labor force participation rates, hours worked, and productivity led to a breakdown in Okun's law during the 1940s. Third, the U.S. labor market worked with astounding efficiency: despite large sectoral shifts at the end of the war, most of the workers who separated from their jobs moved directly into new jobs without experiencing unemployment. All of these factors lined up to create a post-war boom despite the largest fall in government spending in U.S. history.

*We are grateful to Claudia Goldin and William Collins for sharing their digitized Palmer data with us. We thank the great team of UCSD undergraduates and Philadelphia Federal Reserve research assistants who digitized and cleaned the data from 2017 to 2023: Johan De Rijke, Cole Dreier, Suzanne Golshanara, Aishwarya Kudrimoti, Ashlee Liu, Anne Park, Madison Perry, Rachel Yang, and Cindy Zhang. We are grateful for helpful comments from Gillian Brunet, Robert Chirinko, Gabriel Chodorow-Reich, Alex Field, Garey Ramey, Allison Shertzer, and Johannes Wieland, as well as participants in the April 2024 NBER WWII conference, the NBER EFG conference, the Robert Gordon celebration conference, the Hoover Institution seminar, the Stanford macro lunch, and the LSE economic history and macro seminars. We particularly thank Robert Gordon and Price Fishback for detailed comments that greatly improved the paper. Valerie Ramey gratefully acknowledges financial support from National Science Foundation Grant No. 1658796. The analysis and conclusions in this paper are the work of the authors alone and do not necessarily represent the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

†Federal Reserve Bank of Philadelphia. E-mail: shigeru.fujita@phil.frb.org.

‡Stanford University Hoover Institution, NBER, and CEPR. E-mail: vramey@stanford.edu.

§Starbucks Global Center of Excellence and MIT FutureTech. E-mail: troded24@gmail.com.

JEL codes: E22, E32, E37, E62, N42
Keywords: World War II, unemployment, gross labor market flows, government spending, pent-up demand

1 Introduction

When World War II ended, government spending collapsed, demand shifted across sectors, and millions of individuals left their wartime jobs for other pursuits. Government purchases, which had been almost half of GDP at the peak of the war, fell by 70 percent within a year and a half. 13 million members of the armed forces were discharged back to civilian life and consumer-focused industries that had converted to war production were seeking to reconvert. Modern macro models that emphasize aggregate demand and labor market frictions predict that those events should have led to a significant rise in the unemployment rate —but that did not happen. After hitting a low of 1 percent in the first half of 1945, the civilian unemployment rate rose to a peak of 4.5 percent in spring 1946 and hovered just below 4 percent for several years until the 1949 recession pushed it to almost 8 percent.

This paper studies why the decline in government purchases and the upheaval to U.S. labor markets at the end of WWII resulted in only a small increase in the unemployment rate. Our analysis requires answering three sub-questions. First, conditional on the 20 percent decline in real GDP, why didn't the unemployment rate rise by 10 percentage points, as predicted by Okun's Law? Second, why did GDP decline by only 60 percent of the decline in government spending, i.e., why was the multiplier only 0.6? Third, how did the labor market reallocate workers so quickly despite the large sectoral shifts in demand? To answer these questions, we use aggregate data, sectoral data, government surveys, and a new longitudinal dataset on thousands of individuals from 1940 to early 1950. With these data, we study the sources of the breakdown of Okun's Law, the reallocation of workers across the economy, and the macro factors that led to robust job creation despite the significant fall in government spending stimulus.

The paper begins by describing the behavior of some key macroeconomic variables of the period in Section 2 and the new data in Section 3. In Section 4, we analyze how and why Okun's Law broke down. We first show that the Okun's Law coefficient was significantly different in the 1940s. To understand why, we use a production function identity and econometric theory to decompose the changes in the estimated Okun's law coefficient into changes in the underlying correlations of key variables with unemployment changes. We find that labor productivity, hours per worker, and labor force participation rates were all significantly more procyclical during the 1940s compared to the post-WWII period. We highlight how the special circumstances of WWII led to their unusual behavior.

Even with the labor force movements, one might still wonder how workers could be allocated so quickly and efficiently during reconversion. In Section 5, we begin by showing a high rate of aggregate labor turnover during the war and after, with substantial reallocation across industries and occupations. To delve more deeply, we turn to our new longitudinal data set based on the Palmer data, which allows us to follow thousands of individuals month by month from the 1940s through 1950, to see how they made the transitions. Like the aggregate data, our dataset shows a large bulge in the separation rate from August 1945 through early 1946. We find that the employer-to-employer movements are the dominant part of gross flows after job separation. Flows from employment to out of the labor force are much smaller and flows to unemployment are even smaller. Distinguishing by whether the separation was from a civilian job or a military discharge, we find that employer-to-employer movements dwarf the other gross flows for civilian workers. For military discharges, armed forces-to-civilian employer movements are the most important, but movements out of the labor force are still sizable.

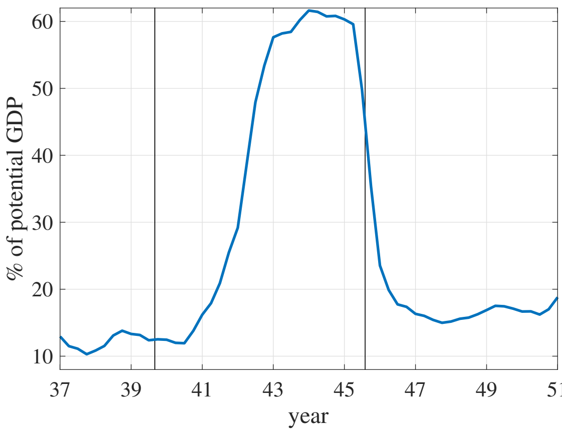
An interesting question is whether the labor reallocation involved climbing or dropping down the career ladder. In Section 6, we study the occupational mobility of workers from before their end-of-war separation or discharge and compare it to afterwards. We find that when soldiers came back from the war, they quickly returned to where they left off in the career ladder (even though most of them changed their employer) and thereafter climbed the ladder steadily. On the other hand, those who were laid off from civilian jobs at the end of the war experienced a significant step down in the occupation ladder, which is qualitatively similar to the one found in the displacement literature using post-war data, e.g., Jacobson et al. (1993), and Davis and von Wachter (2011). But quantitatively speaking, its magnitude and persistence are much less dramatic. The overall pattern is thus in line with the interpretation that their occupation standing was temporarily boosted during the war and dropped to the level consistent with the peacetime economy.

The high rate of transition between jobs was only possible because new private sector jobs were being created. Thus, in Section 7 we turn to the question of what factors led to abundant job creation at the end of the war. Numerous contemporary economists, forecasters, and policymakers worried that the economy would fall back into depression once the massive war stimulus evaporated. In contradiction to those predictions, the economy boomed as private demand for goods and services filled the gap. We discuss possible macroeconomic factors that could have accounted for the burst in private demand, including pent-up demand accompanied by accumulation of financial assets during the war and the Federal Reserve's low interest rate policy. We find that the accumulation of financial assets and interest rate channels do not appear to be explanators. We focus on the pent-up demand story by itself and analyze it in a modern dynamic general equilibrium model. We demonstrate using a simple dynamic neoclassical model that one does not need the financial factors or Keynesian amplification to explain the burst in demand. In our story, WWII sowed the seeds of the post-war boom. Specifically, war spending crowded out investment in private capital stocks (including consumer durable goods) during the war, resulting in capital stocks at the end of the war that were substantially below their steady-state values. When government purchases fell at the end of the war, it freed up production capacity and basic market forces caused private investment to surge in order to bring capital stocks up to the balanced growth path.

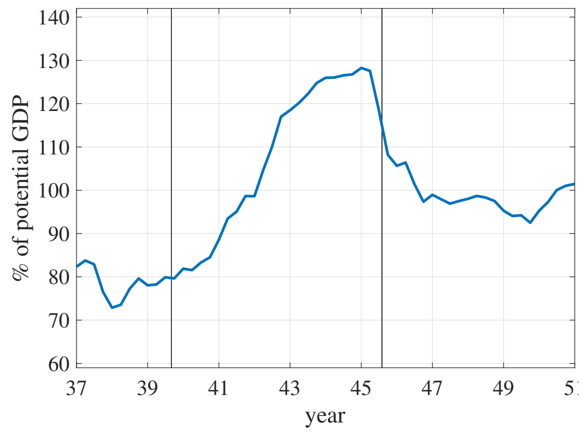
2 Backdrop of the Period

The U.S. economy of the 1940s was exceptional both because churning and sectoral reallocation were unusually high and because it ushered in changes in labor markets that persisted for decades. Figure 1 shows the behavior of real government spending and real GDP during WWII, expressed as the values relative to potential GDP. As noted in the introduction, real government spending rose at the start of WWII and then fell quickly after its end. Real GDP fell by 20 percent, but remained significantly higher than the pre-war period, even after

Figure 1: Real Government Spending and Real GDP During WWII



(a) Real Government Spending

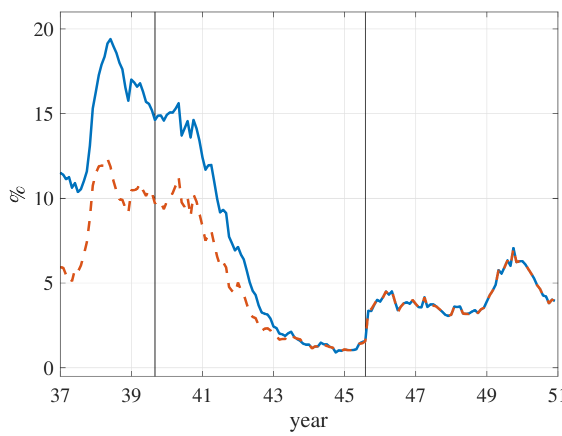


(b) Real GDP

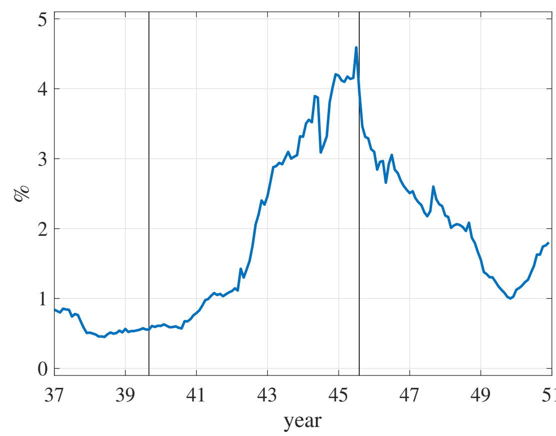
Notes: Both series are divided by potential GDP. Vertical red lines show start and end of WWII. Data from Ramey and Zubairy (2018)

adjusting for the growth in potential GDP.

Figure 2: Monthly Unemployment Rate and Vacancy Rate



(a) Unemployment Rate

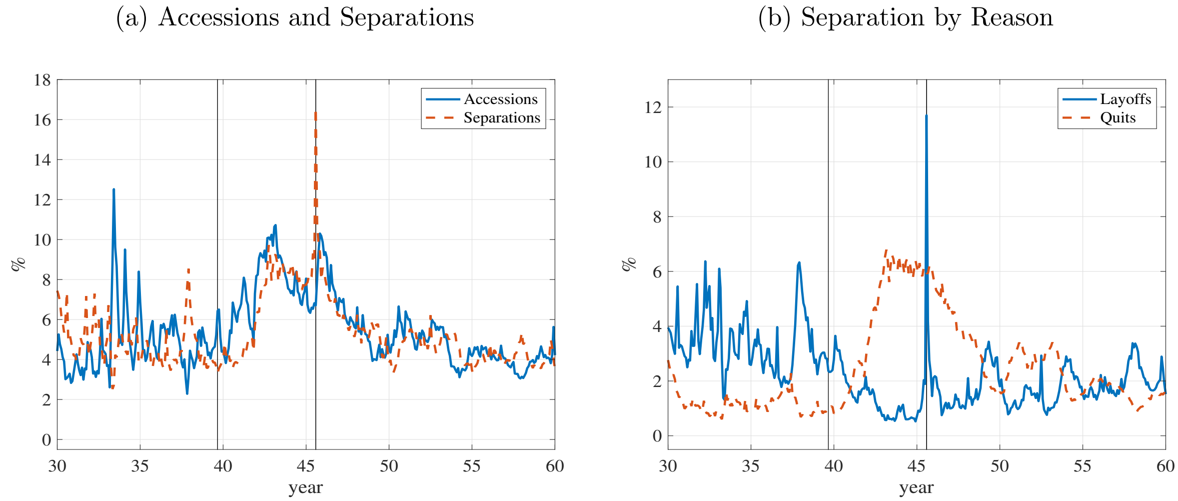


(b) Vacancy Rate

Notes: Left panel: Seasonally adjusted civilian unemployment rates, based on unadjusted data from the NBER Macro history database and Census Bureau's *Current Population Reports*. The higher rate classifies emergency workers as unemployed; the lower, as employed. The vacancy rate is seasonally adjusted and is based on data from Zagorsky (1998).

The left panel of Figure 2 shows the unemployment rate. When the war ended, the unemployment rate rose by three percentage points to its peacetime natural rate rather than

Figure 3: Manufacturing Labor Turnover Rates



Notes: The series are seasonally adjusted version of variables from the BLS, downloaded from the NBER Macro History Database.

spiking up as was widely expected at the time. Okun's Law implies that the 20 percent decline in GDP should have led the unemployment rate to rise by 10 percentage points instead of the actual three percentage points.

The right panel of Figure 2 shows that the vacancy rate rose significantly during WWII and declined at the end of the war, though it remained higher than its pre-war level. This is notable since in the post-war period such large declines in the vacancy rate have always been accompanied by similarly large increases in joblessness. A better understanding of this episode may provide important insights into modern labor market debates on whether job vacancies can fall without inducing a large increase in the unemployment rate even if the economy slows down. [1]

Figure 3 shows turnover rates in manufacturing. Gross flows rose significantly during the war, with both accession and separation rates rising to unprecedented levels. They gradually returned to normal levels by 1948. The end of the war in August 1945 resulted in a dramatic spike in the layoff rate. During the war, the quit rate increased six-fold and then fell after the war.

[1] See Blanchard et al. (2022) and Figura and Waller (2022) on this debate.

3 Data Sources

Our analysis uses a variety of data sources to uncover the factors behind the small rise in the unemployment rate. The main data source is a new longitudinal version of the Palmer data. However, because these data are not nationally representative, we augment our analysis with other data sources to paint a more complete picture.

3.1 The Palmer Data

In January and February 1951, Gladys Palmer of the University of Pennsylvania, in conjunction with the Census Bureau, conducted a survey of individuals in six cities: Philadelphia, New Haven, St. Paul, Chicago, San Francisco and Los Angeles (Palmer and Brainerd (1954)).[2] In the first interview, limited information was gathered for all members of each sample household. The original sample was representative for the six cities (not including the greater metropolitan area). A second interview gathered detailed work history data for 13,555 individuals who were ages 25 and over at the time of the interview and who had worked at least one month in 1950.

A number of economists and sociologists analyzed the data in the 1950s through the 1970s but it was forgotten until Claudia Goldin rediscovered some of the original records and arranged for them to be archived. Goldin (1991) digitized and analyzed some of the information on women from the front of the transcription cards and Collins (2000) did the same for many of the men. The front-of-the-card information they used includes background demographics, detail about current, first, and longest employment, as well as snapshots of a couple points in time during the 1940s. However, during our visit to the archives, we discovered additional information on the back of the transcription cards. The back-of-card information contains spells that detail the entire labor market history for each individual, at least from 1940 and often before. Each spell contains data on the start date (month

[2]The study was designed in conjunction with the research labs of seven major universities (UChicago, the University of Pennsylvania, UCLA, Berkeley, Minnesota, Yale, and MIT) to ensure accuracy of the collected data. The six cities the survey was conducted in were themselves chosen in part because of the location of these prominent research labs.

Table 1: Availability of the Palmer Data

City	Sex	Original Sample	Front Available	Front % of Original	Back Available	Back % of original
Chicago	Men	1,679	1,253	74.6	0	0
	Women	826	768	93.0	768	93.0
Los Angeles	Men	1,330	1,261	94.8	1,261	94.8
	Women	671	639	95.2	639	95.2
New Haven	Men	1,597	1,510	94.6	1,509	94.5
	Women	776	711	91.6	711	91.6
Philadelphia	Men	1,591	1,495	94.0	1,495	94.0
	Women	688	640	93.0	640	93.0
San Francisco	Men	1,457	1,302	89.4	184	12.6
	Women	808	726	89.9	0	0.0
St. Paul	Men	1,500	1,437	95.8	0	0.0
	Women	632	599	94.8	0	0.0

and year), end date (month and year), and reason for leaving that spell. Employed spells provide the 3-digit occupation and industry codes, employer name, job title, and employment location (city and state). Non-employed spells specify the activity, e.g., looking for work, keeping house, retired, etc. Using these spell data, we created a consistent monthly panel on labor market status, occupational standing, and geographic mobility from January 1940 to January 1951 period.

Of the 13,555 individuals interviewed for the Palmer sample, we have front-of-card information for 12,341 and back-of-card information on spells for 7,207. Table 1 summarizes the availability of the information by city. Our main analysis uses the back-of-the-card information and thus is mostly based on the individuals residing in Los Angeles, New Haven, and Philadelphia as of early 1951.

There are a few obvious limitations to our dataset. The first is that the surveyers' sample selection rule required that individuals work at least one month in 1950. As a result, individuals in our sample are more likely to be "attached" to the labor market. Moreover, the dataset does not capture women who were drawn into the labor force during WWII and later become housewives after the war. Second, the labor market spells in our dataset are

Table 2: Comparison between Palmer Panel and 1950 Census

	Palmer Panel	1950 Census			
		U.S.	Six Cities	U.S., Worked	Six Cities, Worked
Male (%)	61.73	49.26	48.35	66.91	62.66
Mean Age (years)	41.92	40.39	41.36	40.20	41.13
Married (%)	70.11	65.34	61.47	61.76	55.20
Foreign born (%)	17.29	11.52	20.23	10.10	18.23
Graduated High School (%)	38.93	12.92	16.10	41.20	46.47
Median income: employed (1950 $)	2,400	1,950	2,350	2,050	2,450
World War 2 Veteran (%)	19.34	4.59	5.39	20.13	20.31
Median weeks worked	48	52	52	52	52
Median weeks unemployed	0	14	14	14	14
Race					
White	87.33	90.17	86.68	89.82	86.70
Black	11.53	9.41	12.10	9.71	11.67
Other	1.14	0.43	1.22	0.46	1.63
Labor Force Status					
Employed	93.17	51.85	54.82	85.01	86.28
Unemployed	2.26	2.10	3.25	3.20	4.79
Not in labor force	4.51	46.04	41.93	11.80	8.93

all based on recalls, going back as far as 11 years before. Nevertheless, we expect "flashbulb memory" effects to make recall more reliable than usual, at least for the turbulent years surrounding WWII. Third, since it is a longitudinal data, the age composition changes over time. Because age is an important characteristic that is correlated with various labor market outcomes, the tabulated results over time are affected by this feature. Fortunately, various U.S. government agencies conducted many rich surveys in the 1940s and thus we augment our analysis with these additional pieces of evidence.

To determine the representativeness of our sample, we first compare it with the 1% 1950 Census data.[3] Table 2 compares major observable characteristics of our panel sample with those in four different samples within the 1950 Census data: (i) total U.S. population, (ii)

[3]While complete county 1950 Census data has just been made available this year, we use weights provided by IPUMS (PERWT) to weigh the observables in the 1% 1950 Census so that data is representative of the 1950 U.S. population. The data were pulled from IPUMS USA (Ruggles et al. (2024))

residents of the six cities, (iii) total U.S. population that worked in the previous year, (iv) residents of the six cities who worked as of January 1950. As noted above, the interviews for the Palmer surveys are conduced only for those who worked one month or more in 1950. Thus, the last sample within the Census data is the most comparable one to our dataset. Comparison within the Census data between overall US population and those who resided in the six cities shows that the effects of the selection due to restricting the sample to the six cities are relatively small, although the share of immigrants (those who are born outside the U.S.) is much higher in those cities, those who reside in those cities earn more, and are somewhat more educated (the share of those who graduated high school), all of which are not surprising. Restricting the sample to those who worked makes more significant differences in average characteristics. Beyond its direct consequence on the composition of population by labor force status, this selection substantially increases the share of males and the education level. However, the comparison between the characteristics of our Palmer dataset and those in the six-city Census sample with a requirement of "employed in the previous year" makes it clear that our Palmer dataset does not suffer from peculiar issues that keep us from using the data for our research question.

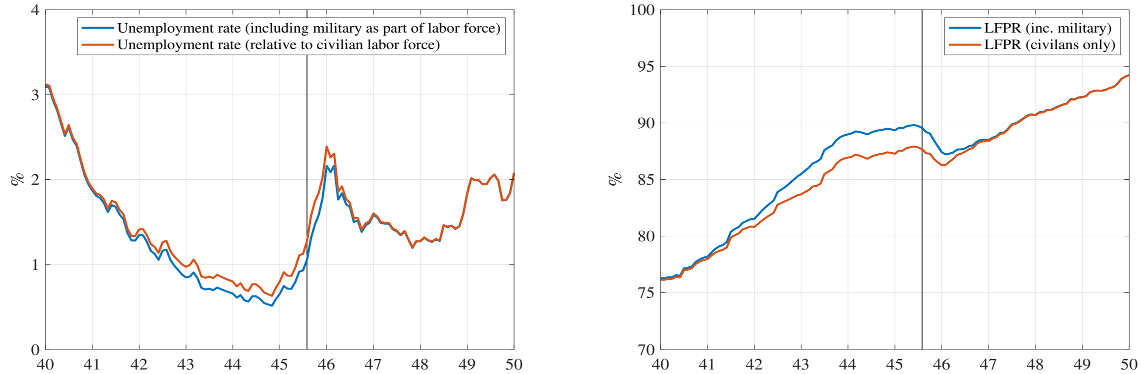
In addition to the cross sectional characteristics, we can also examine basic time series properties of our data with respect to the the official labor market series compiled by the Census.[4] Figure 4 plots the overall unemployment rate and the labor force participation rate in our data.[5] Relative to the official series plotted before, the unemployment rate in the Palmer data has a lower level. This is again due to the sample selection that required having a job in 1950. Nevertheless, the time series pattern is overall similar. Especially, the unemployment rate dropped steadily in the first half of the 1940s, reaching a very low level in early 1945. From there on, it increased sharply but did so for a brief period. It peaked already at the beginning of 1946 and settled at a relatively low level. The selection issue in the Palmer data has even larger impacts on the labor force participation rate. The overall

[4] The U.S. Census published monthly labor force statistics in the *Current Population Reports*, which were the precursor to the Current Population Survey (CPS) later conducted by the BLS.

[5] Note that as mentioned above, both measures count military toward the labor force.

Figure 4: Labor Force Data in the Palmer Data

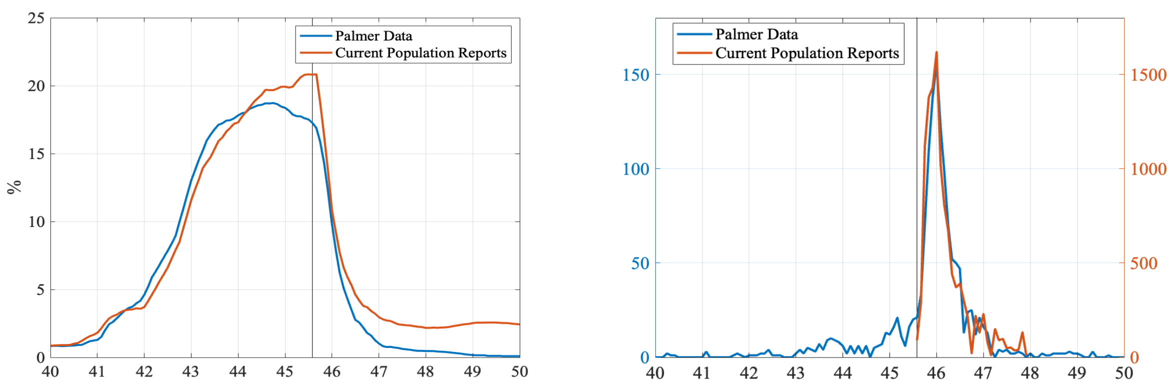
(a) Unemployment Rate (b) LFPR



Source: Palmer data.

Figure 5: Share of Military and Discharges

(a) Share of Military Personnel in Total Employment (b) Discharges



Source: Palmer data; estimates based on *Current Population Reports* data.

level is much higher than the official series and it converges to 100 percent toward the end of the sample. However, the Palmer data retains the key aspect that the participation rate dropped sharply after WWII although the decline is much larger in the BLS series.

Lastly, another obvious aspect we would like to capture is the entry into and exit from the armed forces. Figure 5(a) compares the share of military employment in our Palmer data and to the share from the *Current Population Reports*. We can see the military employment share in our dataset closely tracks the Census series. In Panel (b), we plot the number of monthly military discharges constructed in our Palmer panel against estimates based on veteran series available in the *Current Population Reports*.[6] Apart from the obvious level differences, our series tracks very closely the officially tabulated series.

Thus, the Palmer data matches the other data sources well for some series. However, for other series, the sample selection in the Palmer data set make the series less representative. For this reason, we also draw on supplemental data sources.

3.2 Supplemental Government Data

In order to insure that we do not draw conclusions from too specific a sample, we also exploit as many other data sources as possible. We already drew on decennial Census data in the last section to compare to the Palmer data. We also use several types of data collected by the U.S. government during the 1940s and early 1950s. First, we draw from the numerous special surveys conducted on the outcomes of workers after the end of the war, the experiences of veterans, and the experiences of women. Second, we heavily use the government's regular surveys of the time, such as the *Current Population Reports* (CPR), which contain rich labor market data for individuals. Third, we use detailed industry data on hiring, lay-offs, quits for manufacturing, as well as sectoral employment data and vacancy rates for the overall economy. With all these data to augment the Palmer data, we can construct a more complete picture of the state of the labor market.

In each of the next sections, we examine the various forces that might explain why the rise in the unemployment rate was so small. We begin with the breakdown in Okun's Law in Section 4, which studies why the unemployment rate didn't rise as much as Okun's Law predicts given the fall in GDP. Section 5 exploits the richness of our Palmer longitudinal data set to study monthly flows of workers across labor market states and across industries to understand the speed of reallocation. Finally, Section 7 uses a neoclassical model to study the macro factors that can explain why job creation was so strong at the end of the war.

[6] Our military discharge series uses the "reason for leaving" code as explained in the next section.

4 The Breakdown of Okun's Law

Okun's Law originally specified that every one percentage point rise in the unemployment rate above the natural rate resulted in three percent less GDP relative to potential GDP (Okun (1963)). Modern versions reformulate the law in terms of GDP growth rates and changes in unemployment and find that a one percentage point rise in the unemployment rate is associated with lower GDP growth by approximately two percent. According to this version of Okun's law, the 20 percent drop in real GDP at the end of the war should have been associated with a 10 percentage point rise in the unemployment rate. [7] Instead, the unemployment rate rose only 3.5 percentage points. Okun (1963) noted that changes in the behavior of labor force participation, hours per worker, and productivity growth could interfere with the otherwise stable relationship between output and unemployment. In this section, we document the instability during the 1940s and trace the deviations to the behavior of these three factors.[8]

4.1 The 1940s Steepening

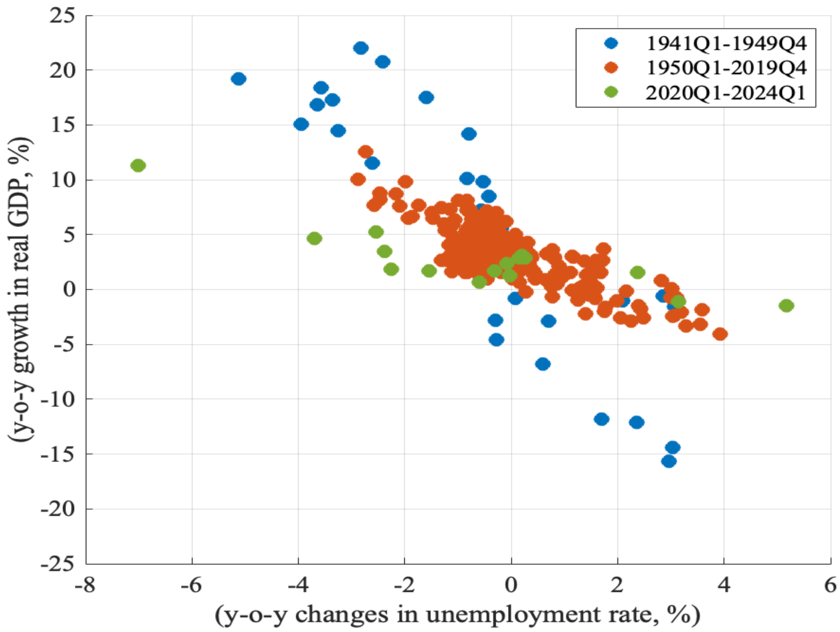
Figure 6 plots year-over-year real GDP growth against year-over-year changes in the unemployment rate. The red dots present the relationship in the post-war and pre-COVID period (1950-2019). When we estimate the slope of this relationship for this period, we obtain the value of -1.93, confirming the rule of thumb of -2. The literature has argued that this relationship has exhibited remarkable stability in the post-war period.[9] While we can visually detect some deviations from this rule in the figure, overall this relationship "held up surprisingly well over time" (Daly et al. (2014)). However, this relationship is not as tight in the 1940s, as indicated by blue dots. Moreover, the slope is clearly steeper in this period

[7]However, as Plosser and Schwert (1979) point out, one can't simply invert a coefficient from the reverse regression. A regression of the change in unemployment on GDP growth from 1948-2019 produces a regression coefficient of -0.4, which implies that a 20 percent drop in real GDP should generate an 8 percentage point rise in the unemployment rate.

[8]We are particularly grateful to Robert Gordon for his suggestions for expanding our analysis.

[9]See, for example, Knotek (2007), Daly and Hoijn (2010), Meyer and Tasci (2012), Owyang and Sekhposyan (2012), Daly et al. (2013, 2014, 2017), and Ball et al. (2017) for the examination of the short-run stability of Okun's law in the post-WWII data.

Figure 6: Okun's Law Relationship



Note: See Appendix A.2 for data sources and data construction details.

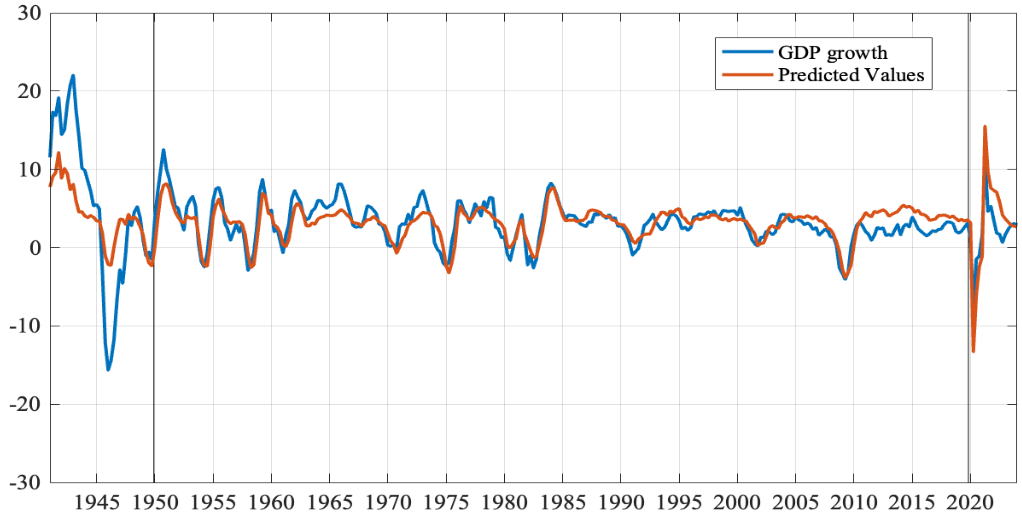
— the estimate is -4.2 — so smaller changes in the unemployment rate are associated with a given percent change in GDP. In contrast, the slope of Okun's Law is flatter during the COVID pandemic period, implying that changes in the unemployment rate were larger than what is implied by the usual Okun's law relationship.

Figure 7 presents the in-sample and out-of-sample fit of the Okun's Law regression estimated over the 1951-2019 period. The fit is very tight within sample, but there are large deviations during the 1940s and the 2020s.

4.2 A Production Function Decomposition

Okun (1963) formulated his law based on a production function approach, though he did not give explicit equations. He proposed that if the deviation of the unemployment rate from the natural rate is a good proxy for the overall utilization rate of other factors of production, then the regression relationship between unemployment and GDP is a useful rule of thumb for translating variations in GDP into variations in unemployment and vice versa.

Figure 7: In- and Out-of-Sample Fit of Okun's Law



Note: Vertical lines in the figure indicate the start (1950Q1) and the end (2019Q4) of the estimation sample. See Appendix A.2 for data sources and data construction details.

We make these relationships explicit using a production function identity:[10]

$$Y_t \equiv X_t\, H_t\, (1 - U_t)\, LF_t\, N_t, \tag{1}$$

where Y_t is real output, X_t is labor productivity, measured by real output per hour, H_t is hours per worker, U_t is the unemployment rate, LF_t is the labor force participation rate, and N_t is population.

We take log differences and use the approximation $ln(1 - U_t) \approx -U_t$ to obtain:

$$dy_t = dx_t + dh_t - dU_t + dlf_t + dn_t + \epsilon_t, \tag{2}$$

where d represents the year-over-year change (using quarterly data) and variables in lower-case letters indicate logged values. The unemployment rate is expressed as a level change to be consistent with the practice in the Okun's law literature. The residual term ϵ_t captures approximation error and measurement error in the data (since the series come from several

[10]We use the form implicit in Okun's description. See Friedman and Wachter (1974), Prachowny (1993), and Daly et al. (2013) for analyses using standard production functions.

different sources).

Assuming no correlation between the error term ϵ and the regressors, Equation 2 implies that a regression of GDP growth on all five variables on the right should produce coefficients of unity on each variable, with a negative sign for the unemployment rate change. However, the Okun's Law regression omits four of the regressors. To link the Okun's Law coefficient estimates to the omitted variables, we use the econometrics of omitted variable bias. It is important to emphasize that the regression coefficients capture correlations but do not imply causality since all variables (except perhaps population) are endogenous macroeconomic outcomes. Our decomposition should be viewed as an accounting exercise designed to pinpoint the statistical source of the change in the Okun's Law coefficient. Rewrite the standard Okun's Law regression as:

$$dy_t = \beta dU_t + \eta_t, \quad \text{where } \eta_t = dx_t + dh_t + dlf_t + dn_t + \epsilon_t, \tag{3}$$

The estimated coefficient on the change in unemployment in Okun's law, β, is equal to the true value of -1 plus "omitted variable bias" terms:

$$\begin{aligned}\hat{\beta} = \frac{Cov(dy_t, dU_t)}{Var(dU_t)} &= -1 + \frac{Cov(dx_t, dU_t)}{Var(dU_t)} + \frac{Cov(dn_t, dU_t)}{Var(dU_t)} \\ &+ \frac{Cov(dlf_t, dU_t)}{Var(dU_t)} + \frac{Cov(dh_t, dU_t)}{Var(dU_t)} + \frac{Cov(\epsilon_t, dU_t)}{Var(dU_t)}.\end{aligned} \tag{4}$$

The covariance terms that make the estimated Okun's coefficient deviate from -1 are equal to the coefficients in a series of bivariate regressions of dx on dU, dn on dU, etc. Thus, the Okun's Law regression will be stable if the sum of the coefficients from these five auxiliary regressions is stable.

To uncover the source of the instabilities in Okun's Law during the 1940s and COVID period, we estimate the auxiliary regressions to obtain estimates of these covariances for three different sample periods: (i) 1940s (1940Q1-1949Q4), (ii) post-war, pre-COVID (1950Q1-2019Q4), and (iii) COVID (2020Q1-2024Q1). The data appendix discusses the data sources for the additional variables.

Table 3 summarizes the results from the regressions. Each column represents a bivariate regression with the change in the unemployment rate as the regressor. The dependent variable in the first column is GDP growth dy, so this is the modern version of Okun's Law regression. The estimates show numerically what we illustrated in Figure 6: the slope is substantially steeper during the 1940s and somewhat flatter during COVID than during the post-war, pre-COVID period. Columns 2 through 5 show the coefficients from the auxiliary bivariate regressions in which labor force participation rates, hours per worker, labor productivity, and the residual term are the dependent variables. As shown in Equation 4 above, the difference between the Okun's Law coefficient in Column 1 and the sum of Columns 2 through 5 is always -1.

The coefficients of the bivariate regressions of the variables on the change in unemployment shown in columns 2 through 5 show how the correlations change. Focus first on the 1950-2019 sample in the middle row. Since the regressor is the change in the unemployment rate, a positive coefficient indicates countercyclicality and negative coefficient indicates procyclicality. Both hours per worker and labor force participation are procyclical whereas productivity is essentially acyclical on average in the postwar sample. However, during the 1940s shown on the top row, all three variables become much more procyclical.

The bottom panel of Table 3 shows the change in the coefficients relative to the 1950-2019 period. Of the -2.3 steepening of the Okun's Law relationship in the 1940s, -0.9 is from labor productivity (dx), -0.8 is from average hours per worker (dh), and -1 is from the change in the procyclicality of the labor force participation rate (dlf). These three variables explain more than 100 percent because the combined population and error term had a flattening effect.

The next section studies the behavior of labor productivity and average hours and briefly discusses possible reasons for their unusual behavior in the 1940s. The subsequent section studies the unusual behavior of labor force participation rates in more detail.

Figure 8(a) shows that labor productivity is very procyclical during the 1940s, rising

Table 3: Decomposition of the Okun's Law Coefficient Estimates

	Okun's law	Auxiliary regressions			
Dependent var.	dy	dx_t	dh_t	dlf_t	$dn_t + \epsilon_t$
1941Q1-1949Q4	-4.27	-0.77	-1.25	-1.25	0.00
1950Q1-2019Q4	-1.93	0.10	-0.42	-0.27	-0.33
2020Q1-2024Q1	-1.08	1.96	0.26	-2.10	-0.20
	Difference from 1950Q1-2019Q4 estimates				
1941Q1-1949Q4	-2.34	-0.87	-0.83	-0.98	0.34
2020Q1-2024Q1	0.85	1.86	0.69	-1.83	0.14

Notes: The top panel shows estimates of the coefficient on the year-over-year change in the unemployment rate in a bivariate regression with dependent variables indicated by the column heading. d denotes difference, y = log real GDP, x = log output per hour, h = log hours per worker, lf = log labor force participation rate, dn = population, ϵ = error term.

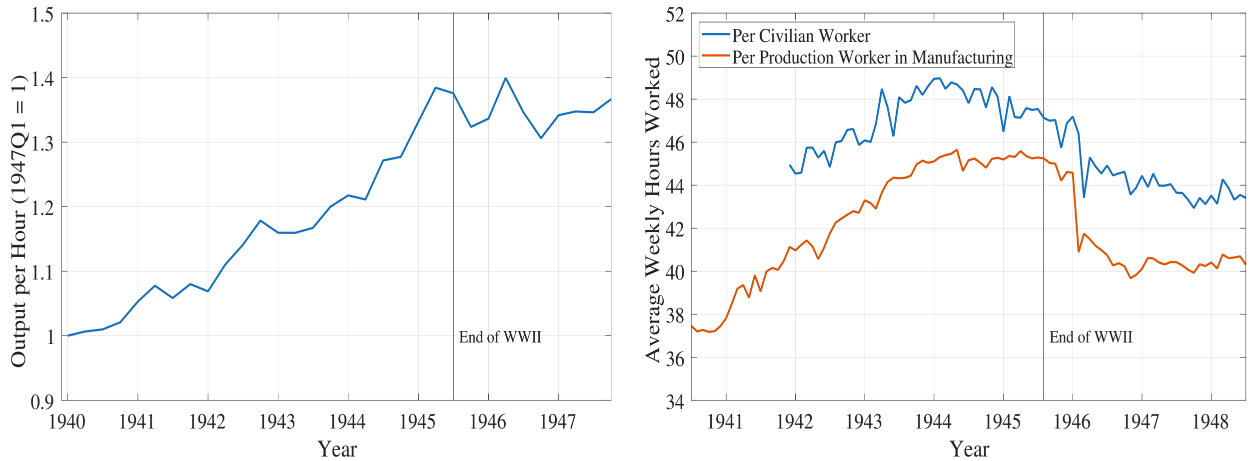
faster than its long-run trend during the war and exhibiting partial reversion at the end of the war. The rise in measured labor productivity during the war is surprising since the rapid rise in hours and the bottlenecks would be expected to reduce labor productivity. Since there were price controls during the war, mismeasurement might play a role. However, other forces such as high effort due to patriotism, longer workweeks of capital, rapid innovation, and learning by doing may also be important. Analyzing the exact sources of the rise and fall of labor productivity is beyond the scope of this paper.

4.3 Productivity and Average Hours

Figure 8(b) shows the significant rise in average hours per worker during the war and the decline at the end of the war. Civilian average hours rose to almost 50 hours per week at their peak, but then fell back below 45 after the war. Manufacturing hours rose from 37 hours per week in early 1940 to 45 hours during the height of the war and fell quickly down to 40 as soon as the war ended. War-time mandates played an important role in raising average hours of work during the war. Executive Order 9301, issued in February 1943, mandated a minimum workweek of 48 hours in factories deemed important to the war effort by the War

Figure 8: Labor Productivity and Average Hours per Worker

(a) Labor Productivity (b) Average Hours per Worker



Notes: XXXXX

Manpower Commission. The order was rescinded on August 20, 1945, and average hours declined soon after.

The combination of the decline in labor productivity and hours per worker at the end of the war meant that more workers were needed to produce each unit of output. Within a year and a half of the end of the war, average hours per worker fell 7 percent and labor productivity fell 6 percent (both in log terms). This means that 13 percent more workers were required to produce a given amount of output.

4.4 Labor Force Participation Rates

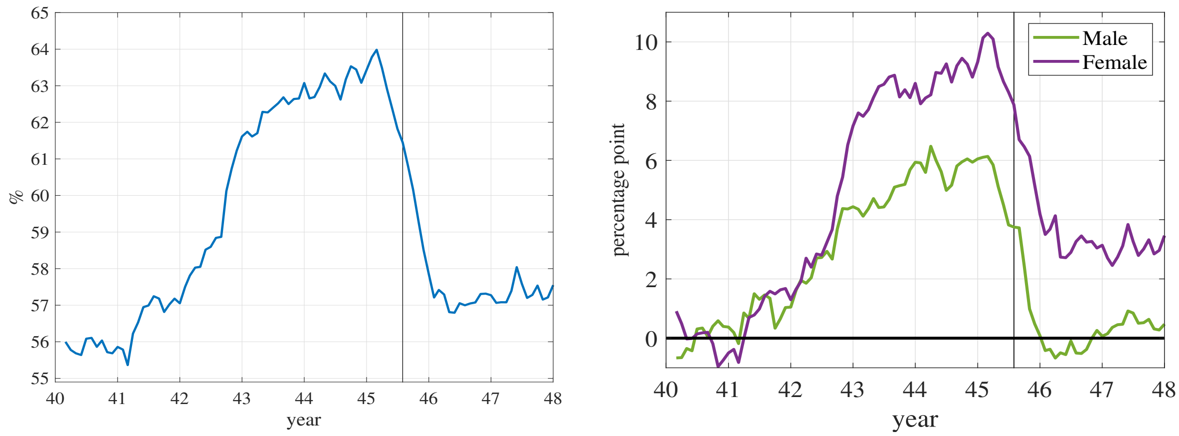
The labor force participation rate was very procyclical during the 1940s. The left panel of Figure 9 shows that the overall participation rate (including the armed forces) rose eight percentage points from 1940 to a peak in early 1945.

The likely sources of the increase are well known. First, conscription, instituted in September 1940, drove a rise in the number in the armed forces to a peak of over 12 million in 1945, which was equal to 12.5 percent of the population ages 14 and above. Second, nonpecuniary factors such as patriotism may have led to part of the rise in labor force participation (e.g. Mulligan (1998)). Third, standard neoclassical theory predicts that the huge

Figure 9: Labor Force Participation Rates

(a) Ages 14+, Including Armed Forces

(b) Change Relative to 1940 Average, by Sex



Note: Based on data from the Census *Current Population Reports*. Seasonally adjusted.

increase in government spending should have created a negative wealth effect that raised labor supply. McGrattan and Ohanian (2010) use a quantitative dynamic neoclassical model that abstracts from the price controls and other government market interventions to argue that pecuniary forces can explain the bulk of the increase in hours worked.

As the war wound down, most of the military personnel were discharged from the armed forces and the patriotism motive was no longer relevant. As the left panel of Figure 9 shows, the labor force participation rate began to decline quickly as the war in Europe came to an end in spring 1945 and the pace accelerated after the war in the Pacific ended in August 1945. By early 1946, the participation rate had already fallen to one percentage point above its pre-war value. The result was a 10 percent shrinkage of the total labor force from the peak in early 1945 to early 1946. More relevant to our decomposition equation, the labor force participation rate declined 7.5 percent (in log points) from the end of the war to the end of 1946. Thus, withdrawals from the labor force help explain the small rise in the unemployment rate immediately after the war.

The end of conscription and patriotic motives naturally reversed most of the labor force participation rate increase during the war, but it's interesting to study which types of workers withdrew from the labor force and why they did so. The right panel of Figure 9 decomposes participation rate increases by sex. The graph highlights two key facts. First, female participation rates rose more than male rates relative to their respective 1940s averages; female rates rose 10 percentage points compared to 6 percentage points for males. Second, while the male participation rate fell to close to its pre-war average, the female participation rate remained elevated at three percentage points above its 1940 average.

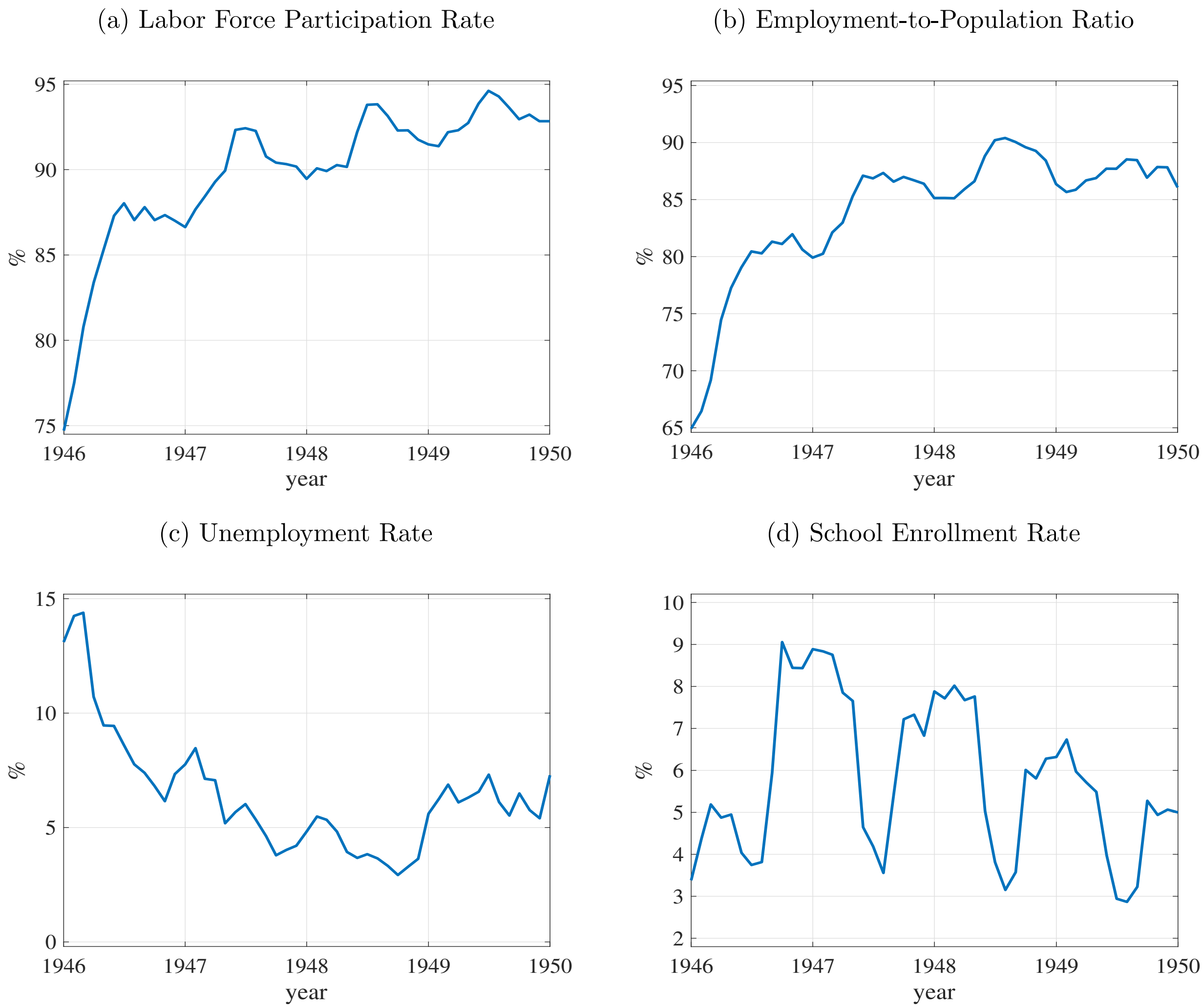
In a separate paper (Fujita and Ramey (2026)), we use our new data to conduct a detailed analysis of the reasons women withdrew from the labor force at the end of the war. The analysis merits a separate paper because of the complexity of the question and its connections to a much larger literature. Here we analyze the behavior of the much less studied movements in male labor force participation rate after the end of the war.

The right panel of Figure 9 shows an undershooting of the male labor force participation rate in early 1946. We trace this undershooting to the behavior of veterans. The number of veterans in the population rose from 2.5 million on VJ-Day (August 1945) to 8.6 million by January 1946 and 13 million a year later (BLS (1946b)). Figure 10 shows the labor force participation rate, employment-to-population ratio, unemployment rate, and percent of population in school for veterans. As the upper left panel shows, the labor force participation rate of returning veterans was only 75 percent in January 1946. In fact, as of January 1946, almost 20 percent of the veterans reported that they were taking vacations before entering the civilian labor force (BLS (1946a)). The timing of the end of the war probably amplified the preference for vacation: the U.S. government strove to discharge veterans as quickly as possible so that many could be home for the Christmas holidays or at least soon after.

For the veterans who had joined the labor force, the unemployment rate was around 14 percent for the first few months of 1946 but quickly declined to 6 to 7 percent by the end of 1946. In late summer/fall 1946, the school enrollment rate of veterans surged to almost 9 percent, aided by the GI bill. We discuss school enrollment in more detail below.

Next consider the behavior of civilian labor force participation rates (LFPR) by sex and age. Table 4 shows these rates for March 1940 vs. March 1945, 1946, and 1947. We compare the March values both because that is the only monthly value available in 1940 and because

Figure 10: Veteran Labor Market Status



Note: Based on data are from the U.S. Bureau of the Census, *Current Population Reports*. The data are not seasonally adjusted.

the data exhibit substantial seasonality. Fortunately, the March 1940 and March 1945 dates are ideal comparisons since March 1940 was several months before the Selective Service Act was passed and March 1945 was around the peak of total labor force participation.

The LFPR of both male teens and males ages 45-64 quickly returned to their 1940 values by March 1946. The rates of those ages 25-44 recovered mostly by March 1946 and completely by March 1947. In contrast, the rates for those ages 20-24 were 16 percentage points below their 1940 values in March 1946 and recovered only partially by March 1947.

Table 4: Male Labor Force Participation Rates by Age (%)

	March 1940	March 1945	March 1946	March 1947
14−19	38	54	38	43
20−24	90	94	74	81
25−44	98	98	94	97
45−64	92	95	93	93
65+	45	52	48	47

Note: Computed from the *Current Population Reports*, Series P-50, no. 2.

A key question is to what extent the 1944 Servicemen's Readjustment Act (GI Bill) depressed labor force participation rates. Table 5 shows the percent of each of the younger age groups enrolled in school as well as the percent enrolled in school and not in the labor force for April 1940 and October 1946. The school enrollment rate of males ages 20-24 rose from 8 percent in spring 1940 to 22 percent in fall 1946. Moreover, 91 percent were veterans (not shown in the table). The school enrollment numbers help explain the slow recovery of male labor force participation among those ages 20-24 — the percent of male 20-24 year-olds in school and not employed rose from 7 percent in spring 1940 to 18 percent in fall 1946, which more than explains the LFPR difference between March 1940 and March 1947 in Table 4. In contrast, one does not see a rise in the school enrollment rates for females. Lennon (2021) shows that female veterans did increase their education as a result of the GI Bill. However, there were only around 330,000 female veterans in contrast to 13 million male veterans, so the effects on female school enrollment rates are necessarily small.

Therefore, the GI Bill was likely an important impetus to the temporary withdrawal of young men from the labor force. This temporary decline in labor supply was a contributing factor to the breakdown of Okun's Law.

To summarize this section on Okun's Law, the unemployment rate did not rise after the war as much as Okun's Law predicted based on the actual decline in GDP. The gap was due to a combination of (i) a decline in labor productivity; (ii) a decline in hours per worker; and (iii) a fall in the labor force participation rate. The first two factors meant that the number

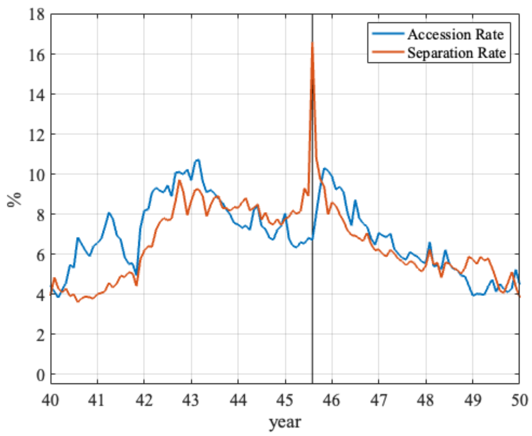
Table 5: Male School Enrollment Rates by Age Group (%)

	April 1940		October 1946	
	In school	In school not in LF	In school	In school not in LF
Ages 14-19	64	59	69	54
Ages 20-24	8	7	22	18

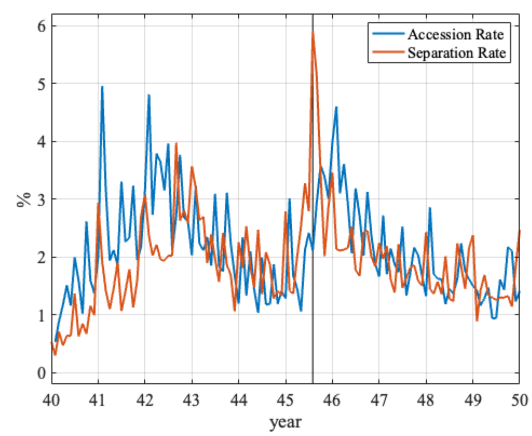
Note: Computed from the *Current Population Reports*, Series P-50, no. 2, Table 1 and no. 14, Table 1.

Figure 11: BLS vs. Palmer Data: Manufacturing

(a) BLS



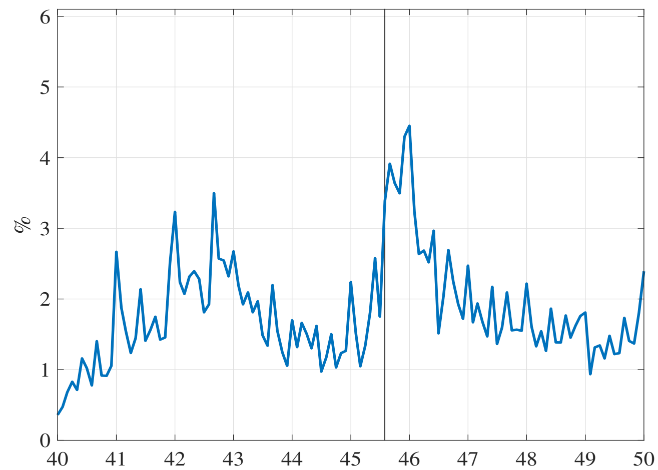
(b) Palmer



Note: Vertical lines indicate the start and end of WWII. *Source*: Palmer data; BLS Manufacturing labor turnover data taken from the NBER macrohistory database.

workers required to produce a unit of GDP rose by 13 percent after the war. The fall in the labor force participation rate reduced labor supply another 7 percent. The unusually high procyclicality of hours and the labor force participation rate during the 1940s was the result of government actions (e.g. mandatory minimum workweeks of factories, conscription, the GI bill) as well as a combination of economic forces and patriotism. While there are case studies of the behavior of productivity at the micro level during the war, understanding the behavior at the macro level requires further research.

Figure 12: Overall Separation Rate in the Palmer Data



Source: Palmer data.

5 Labor Reallocation in the 1940s

We now exploit the richness of our newly created Palmer panel to document the roles played by various gross labor market flows in reallocating labor. We show that the majority of those who separated from their employer moved directly into another job.

In the Palmer survey, each respondent gives a full history of his/her labor market spells. If employed, the respondent gives his/her employer name as well as occupation and industry, which are translated into 3-digit 1950 Census codes. If nonemployed, their occupations are described by their main activity such has "looking for work" or "housewife" or "student" or "taking it easy," allowing us to classify them into either being unemployed or out of the labor force. In addition, the respondents are asked to give a "reason for leaving" when a job spell ended.[11] We hand-coded various descriptions of reasons for leaving into numerical codes. These reason-for-leaving codes allow us to examine the flows based on underlying reasons for separations (instead of those based on the changes in labor market states), giving us additional insights into economic motives behind the labor reallocation process.

To show that the Palmer sample reflects economy-wide patterns, we first compare our

[11]This includes cases such as a change in occupation within the same employer (for example, as a result of promotion) or a transfer to a different plant within the same employer.

accession and separation series constructed from the Palmer data to nationally representative data. In Figure 11, we compare turnover rates in the manufacturing sector in our data to the BLS turnover data for manufacturing (NBER Macrohistory database, (Feenberg and Miron (1997)). While the turnover levels are much lower in our dataset, they share key time-series features with the BLS series. In addition to the selected nature of our dataset, the retrospective nature of the survey is likely to contribute to the low level of overall turnover. When recalling events over the previous ten years, the respondents were likely to forget short-term job or non-employment spells during the interview. In contrast, the BLS labor turnover series are based on the survey of establishments conducted every month and thus likely to capture almost all turnovers, including the cases in which workers are rehired after short non-employment spells. The overall similarity of the time-series pattern gives us confidence that our dataset, despite the small sample size and the geographical concentration, captures important characteristics of the labor market conditions in the 1940s.

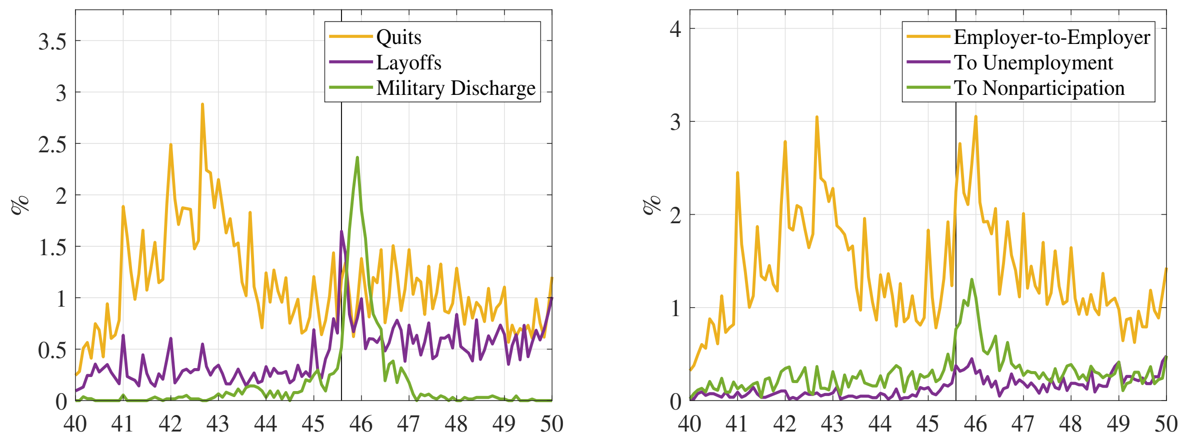
Figure 12 presents the overall separation rate in our data. As explained above, separations here encompass all types of separations. The overall separation rate steadily increased during the first few years of the decade and then dropped through until 1945. As the war came to an end, the separation rate spiked up. Although it came down sharply in 1946, it remained relatively elevated for the following few years.

In Figure 13 (a), separations are divided into three broad categories based on underlying reason: (i) quits, (ii) layoffs, and (iii) military discharges. The figure shows that the spike in the overall separation rate at the end of the war is largely due to military discharges and layoffs, not surprisingly. It is interesting to note, however, that quits increased toward the end of the war and remained elevated for the following two years or so, while the other two reasons for leaving dropped sharply after the initial spike.

In Panel (b), we divide separations based on the worker's destination by labor force status: (i) a different employer (E2E), (ii) unemployment (looking for work) (EU), and (iii) nonparticipation (EN). It shows that the spike of the overall separation rate is absorbed by transitions to different employers without non-employment spells in between. Transitions to

Figure 13: Separation Rates by Reason and Labor Force Destination

(a) Separation Rate by Reason (b) Separation Rates by Destination



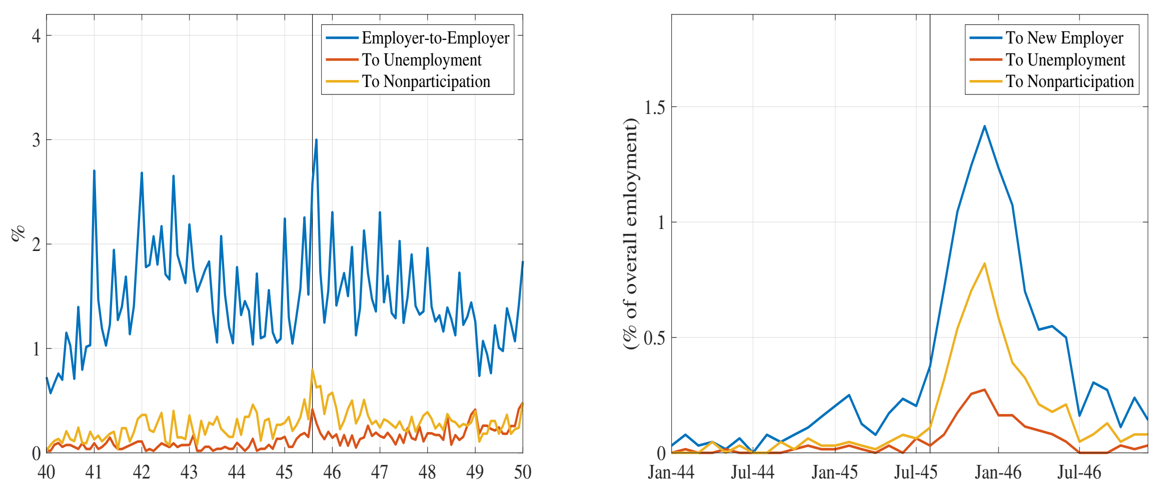
Source: Palmer data.

nonparticipation are also substantial and the smallest share enters into the unemployment pool, looking for the next job. A similar pattern holds when we examine transitions from civilian jobs only (Figure 14 (a)).

In Table 6, we cross tabulate separations by reason and labor force status, pooling all separations that occurred in 1945 and 1946. Each number in the table gives the probability (expressed in percent) of making either (i) E2E or (ii) EU or (iii) EN transition conditional on each reason listed each row. For comparison purposes, we present these probabilities for 1947-1948 in addition to the period at the end of or immediately after WWII (1945-1946). Focusing on the period 1945-1946, we can see that, regardless of the reason for separation, a vast majority of separated workers make E2E transitions without non-employment spells. Even among those who were laid off, more than 70 percent were able to find their next employment right away. The ease with which workers who involuntarily lost their job found their next job immediately was an important force in keeping the unemployment rate from increasing. Another mitigating factor was the propensity of laid off workers who did not immediately find another job to transition to nonparticipation rather than unemployment. A similar pattern holds for the cases of military discharges but the difference in the shares in favor of dropping out of the labor force instead of looking for work right away after the

Figure 14: Civilian Separations and Military Discharges

(a) Separation rates (civilian workers) (b) Military discharges



Source: Palmer data

Table 6: Cross Tabulation of Reason and Labor Force Status after Separation

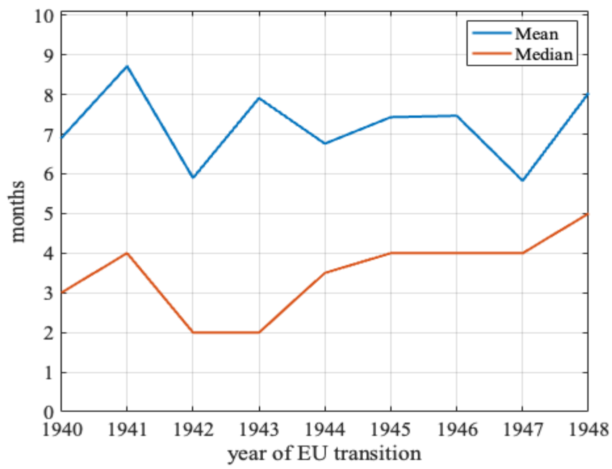
Reason for Separation	1945−1946 E2E	1945−1946 EU	1945−1946 EN	1947−1948 E2E	1947−1948 EU	1947−1948 EN
Quit	71.9	5.1	23.0	73.1	6.7	20.1
Layoff	70.7	13.1	16.2	70.7	17.6	11.7
Military Discharge	63.5	9.1	27.5	75.9	13.0	11.1

Source: Palmer data.

military services is even larger. Moreover, this pattern disappears in the later period in which the EU transitions constitute a larger share of both layoffs and discharges. The importance of transitions into nonparticipation in 1945-1946 highlight the importance of the labor supply factors in avoiding projected increases in the unemployment rate.

We just saw that the gross flows into unemployment were low. Another important determinant of the size of the unemployment pool is how fast jobless workers find their next jobs. Figure 15 plots mean and median completed duration of unemployment among those who made EU transitions that occurred in the year on the horizontal axis. First of all, the levels of these duration measures are relatively high compared with duration measures available

Figure 15: Unemployment Duration By Year of Separation



Source: Palmer data

for the post war period.[12] This level difference is likely due to the fact that the information about each spell is collected retrospectively for the previous 10+ year, thus resulting in the omission of temporary job spells that happened during a long unemployment spell. The other possibility is that the reallocation of labor during the 1940s was more likely to have involved geographical mobility, which include interstate migrations (BLS, Bulletin No. 876). However, a more importantly feature of the data for our purpose is that neither of these measures show a clear run-up toward the end of or immediately after WWII. In the post-war data, unemployment duration consistently and robustly show very strong countercyclicality.

In sum, our longitudinal data has revealed that both the gross flows into unemployment were low and that, even among those who found themselves unemployed, the duration of unemployment was relatively short. For the vast majority of workers who did not withdraw from the labor force, a separation from a job for whatever reason typically resulted in an immediate transition to a new job.

[12]For example, mean unemployment duration measured in the Current Population Survey, which starts in 1948, was about 10 weeks between 1948 and 1950.

6 Career Evolution After WWII

The last section documented the ease with which individuals transitioned from job to job, but the question arises about the quality of the jobs they found. An important aspect of labor reallocation is that it involves climbing or dropping down their career ladder. In this section, we characterize the survey respondents' experience in this respect. Unfortunately, our dataset does not include earnings information. Instead, we use the occupation score variable constructed by IPUMS (Ruggles et al. (2024)) that gives the median income of each occupation (in 1950 dollars) within the 1950 Census occupation classification scheme. We assign the 3-digit occupation scores to the occupation codes in our data. Each occupation is ranked based on the median income and thus the data provides a conceptual linkage to the notion of climbing/dropping a career ladder.

6.1 Veterans

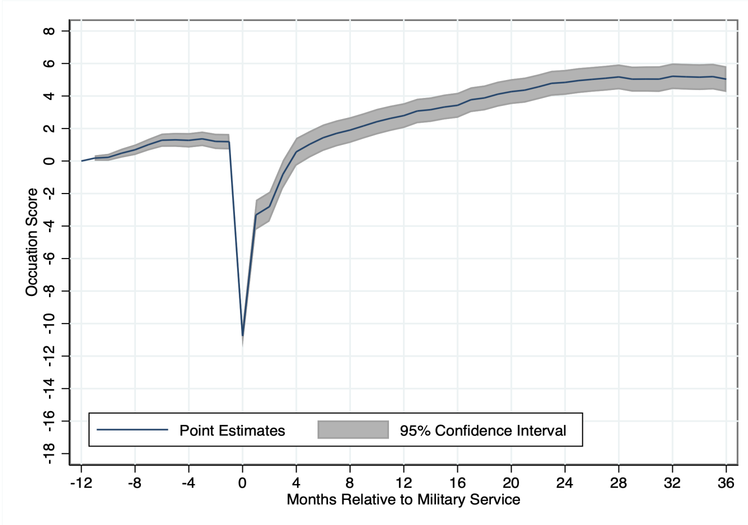
First, we summarize the experiences of veterans when they return from the war by estimating

$$oc_{ik}^{v} = \alpha_i^v + \sum_{k=-12}^{36} \delta_k^v D_{ik} + u_{ik}^v, \tag{5}$$

where oc_{ik}^v is the occupation score of the individual (WWII veteran) i in month k, α_i^v is the individual fixed effect, D_{ik} are dummy variables that take 1 in the worker's kth month and 0 otherwise, u_{ik}^v represents the error term. Note that k is calculated as time relative to their military service and $k = 0$ corresponds to their military spell, during which the occupation score is fixed at 11 using the IPUMS score. We estimate (5) by taking the history of those who had military experiences, starting 12 month before the military spell and ending 3 years later. The regression is estimated on the balanced panel of 1,344 veterans.

Figure 16 plots the coefficient estimates together with the 95% confidence intervals. The score in the first month of the history is taken to be the base level, and thus the results are expressed as the differences from the base level. The score at time 0 drops sharply because the occupation score of "armed service operatives" is much lower than other occupations.

Figure 16: Evolution of Occupation Scores Among WWII Veterans



Source: Palmer data; Occupation scores for the Census 1950 occupation scheme are taken from IPUMS USA (Ruggles et al. (2024)).

Also note that when the individual is jobless (either looking for work or being out of the labor force), the occupation score drops to 0. One can see that veterans' occupation scores quickly recover and eventually surpass the pre-service scores within 8 months after the discharge. Note that the recovery path right after the discharge results from the fact that there was a large share of veterans that did not take the job immediately after the discharge and they returned to working gradually. When we explicitly control for the effects of non-employment (by including the dummy variable in the regression), then the score jumps to the level that exceeds the pre-service level and then follows the shallow upward trajectory as in Figure 16. Thus, the overall upward path of the score appears to show a steady progression of their career even with its interruption due to the war.[13]

The worker's age plays an important role in the overall upward trajectory since they tend to be younger individuals. We control for this effect by interacting D_{ik} with the age-group dummy that takes 1 when a worker is over 30 in 1945 and 0 otherwise. In this regression, the upward slope largely disappears for those that are over 30 in 1945.

[13] Note, however, that the current analysis does not attempt to identify the path of the (counterfactual) control group.

Table 7: Industry Switching After Military Services

	Shares (%) Before ($k = -12$)	Shares (%) After ($k = 36$)
Agriculture	2.3	1.0
Mining	0.3	0.2
Construction	5.7	7.9
Durable Goods Manufacturing	33.2	19.3
Nondurable Goods Manufacturing	11.5	14.1
Transportation, Communication, and Utilities	8.5	10.9
Wholesale and Retail Trade	21.2	23.9
Finance, Insurance, and Real Estate	2.0	3.1
Other Services	12.3	13.2
Public Administration	2.9	6.6

Source: Palmer data.

Table 7 shows how the veterans switched their industries after the military services. There is clearly a large shift from durable goods industries to all other major industries especially to services. The result here is largely consistent with a similar calculation presented in Department of Commerce (1947) (the *Current Population Report* P.50 No. 1).

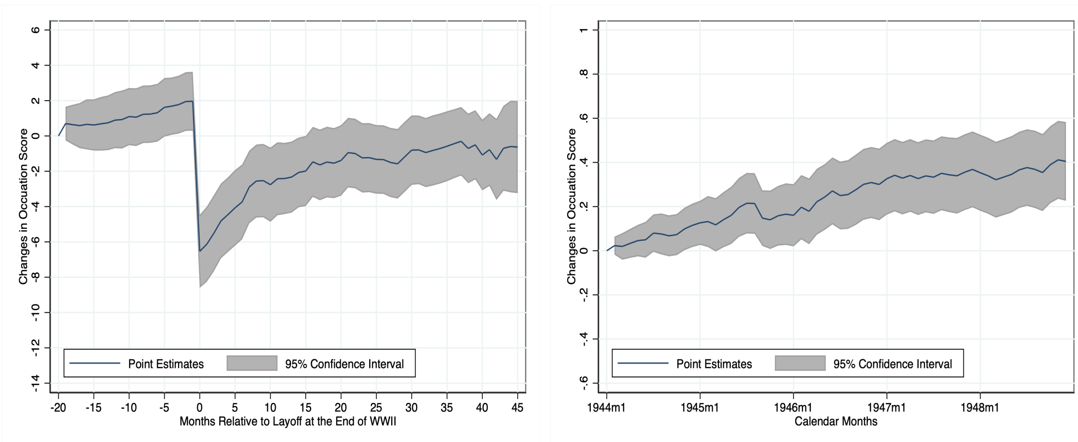
6.2 Displaced Workers

Next, we characterize the experiences of civilian workers who are laid off due to the end of WWII. As we saw before, layoffs spiked toward the end of WWII. Specifically, we take those who were laid off between January 1945 and August 1945 and track their occupation scores. The sample starts one year before the displacement and ends four years after the displacement. For this analysis, we include a control group in our estimation sample. That is, we include workers who did not experience layoffs between January 1945 and August 1948 and remained employed throughout the entire period.[14]

[14] We track 5-year histories of those that are laid off, relative to the month of job loss which varies with individuals. We track workers in the control group roughly the same length of time.

Figure 17: Evolution of Occupation Scores (Civilians)

(a) Layoffs (b) No Layoffs



Source: Palmer data; Occupation scores for the Census 1950 occupation scheme are taken from IPUMS USA (Ruggles et al. (2024)).

We augment the regression equation (5) with the control group data as follows:

$$oc_{it}^c = \alpha_i^c + \gamma_t^c + \sum_{k=-24}^{48} \delta_k^c D_{ik} + u_{it}^c. \tag{6}$$

The difference from the previous equation is that this specification identifies the path of occupation scores of those without the displacement via the individual fixed effect (α_i^c) and the time dummies (γ_t^c), and those with the displacement with the coefficients (δ_k^c) on the dummies that are defined relative to the the layoff event. The regression is estimated on the sample of 4,213 individuals (306 individuals that experienced a layoff due to the end of WWII plus 3,907 individuals in the control group as noted above). There is a large literature on earnings losses of displaced workers that uses post-war data, pioneered by papers such as Ruhm (1991), Jacobson et al. (1993), Stevens (1997), and more recently studied by Davis and von Wachter (2011) who consider a specification similar to (6).

Figure 17 (a) presents the path of the occupation score relative to its initial level. We can see that at the time of layoff, the average occupation score drops sharply. As we saw above in Table 6, layoffs are not equal to transitions to being jobless. Nevertheless, the sharp drop in the score is largely driven by those who experienced a transition to non-employment (which results in the score to drop to 0). After the sharp drop, it gradually increases over time, but never exceeds the initial level. This pattern is qualitatively similar to the one reported in the literature that uses post-war data, which emphasizes the persistent adverse effects that a displacement causes on a worker's subsequent earnings. However, quantitatively speaking, the magnitude of earnings losses here is much smaller than the estimates based on the analysis of the post-war data.[15] Another important feature of the figure is that the occupation standing steadily increased leading up to the layoff event. Note that the existing literature consistently finds gradual declines in earnings shortly before the displacement event. Thus, the overall pattern in our dataset appears to be more in line with the interpretation that workers' occupation standing was temporarily boosted during the war and dropped to the level consistent with the peace-time economy, rather than the interpretation that workers are permanently scarred by displacement, as emphasized in the existing literature.[16]

Panel (b) presents the results for the control group, showing that the occupation scores increased gradually throughout this period. One interesting characteristic of the no-layoff sample is that the occupation score accelerated in the first half of 1945 and then dropped immediately after the war. This pattern is consistent with temporary improvements in occupation standing at the peak of war-related production activities.

6.3 Reconversion and Industry Reallocation

The end of the war meant that the industry structure of the economy had to re-adjust to civilian production, which required a large amount of reallocation of workers and capital away from war-time production toward civilian production. By using gross measures of industry reallocation, this section shows how extensive labor reallocation forces were in the aftermath

[15] Of course, we must remember that the occupational scores in our dataset are not directly comparable to the actual earnings available in post-war datasets.

[16] However, the fact that our regression is based on occupation scores (i.e., median incomes by occupation) limits the comparability of our results with those in the existing literature. For instance, the declines in earnings after a displacement could be driven by reduced hours but occupation scores do not capture this effect.

Table 8: Changes in Industry Composition (Hubbard (1947))

Employment Shares (%)	1939	1944	1946
Manufacturing	33.2	43.1	36.3
Mining	2.8	2.1	2.1
Construction	5.8	1.7	4.9
Transportation and Utilities	9.6	9.5	10.0
Trade	21.8	17.7	19.6
Other Services	13.7	11.0	13.1
Government	13.1	14.9	13.7

Notes: Within non-agricultural industries. Reproduced from Hubbard (1947) Table 3. Original source is Federal Reserve Bulletin.

of WWII. Our analysis highlights the uniqueness of this period, especially in light of the literature that emphasizes the reallocation shocks as an important driver of unemployment (Lilien (1982) and Brainard and Cutler (1993)).[17]

Before examining gross industry reallocation, Table 8, taken from Hubbard (1947), compares the industry composition of the economy, before (1939), at the peak of (1944), and after the war (1946). As one can see, at the peak of war production, the share of manufacturing expanded greatly relative to the pre-war period, drawing workers from pretty much all other industries except for the government sector, which also expanded. By 1946, the manufacturing sector had shrunk by more than 6 percentage points. The fact that the industry composition in 1946 overall is similar to the one in 1940 suggests that the large part of the adjustment process was completed by then. Hubbard (1947) indeed claims that reconversion was completed by September 1946. He presents various pieces of evidence that the physical process of reconversion, such as the changeover of plant and equipment and shifting of labor from the production of war items to peace-time items, progressed very quickly.[18]

The net changes in the employment stocks and the rapid completion of reconversion of physical capital do not directly suggest that the overall impacts on the reallocation of labor were small. We now turn to our Palmer data to examine gross reallocation of workers

[17] See Chodorow-Reich and Wieland (2020) for a more recent examination of this hypothesis.

[18] According to Table 2 in Hubbard (1947), about half of the industries that gone through the reconversion process reported that it would take less than a month for their production to return to a breakeven rate and all industries reported that they would be able to return to full capacities within a year.

Table 9: Changes in Industry Composition (Palmer)

Employment Shares (%)	1940	1944	1946
Manufacturing	33.5	34.9	36.0
Durables	17.4	23.3	20.1
Nondurables	16.1	11.6	15.9
Mining	0.4	0.1	0.1
Construction	6.0	2.9	5.0
Transportation and Utilities	8.6	6.9	8.7
Trade	22.5	14.2	20.7
Other Services	24.3	17.4	22.0
Government	4.8	23.6	7.5

Notes: As of August each year. Sample size: 5,259 (1940), 6,326 (1944), 6,161 (1946).

around this period. Before doing so, Table 9 presents the industry composition within our dataset, including the breakdown of manufacturing into durable and nondurable manufacturing. Relative to Table 8, we see much larger swing in the size of the government sector, while the changes in the manufacturing sector is not as pronounced. However, the other features of the data are similar. We can also see that there is a large shift in employment within manufacturing between its two sub-sectors.

To see the extent of gross industry reallocation, we focus on the sample of individuals who were laid off between January 1945 and August 1945. In Table 10, we present the industry composition of those displaced workers at three data points: 12 months before the layoff, 12 months after the layoff, and three years after the layoff. This restricted sample of displaced workers is small, with only 290 individuals. The distribution of workers prior to the displacement is highly concentrated in the durable goods manufacturing sector. The industry composition after the layoff, shown in the second column, is dramatically different from the one before the layoff. But the changes between one year after the layoff and three years later are fairly small, suggesting that labor reallocation is indeed more or less completed by late 1946.

Table 11 looks explicitly at the share of industry switchers and stayers and also includes those who are not employed (either unemployed or nonparticipants) at the same points in time (12 months later and 36 months later). We see that 86 percent of those who are laid off

Table 10: Changes in Industry Composition Among Displaced Workers

Employment Shares (%)	12 Months Before Layoff	12 Months After Layoff	36 Months After Layoff
Manufacturing	71.3	45.9	42.8
Durables	64.4	24.1	21.9
Nondurables	6.9	21.8	20.9
Mining	0.4	0.0	0.0
Construction	3.8	9.0	9.3
Transportation and Utilities	2.4	3.9	4.7
Trade	6.9	24.5	23.2
Other Services	9.3	14.8	18.0
Government	5.9	2.0	2.2

Notes: Those who are laid off between January 1944 and August 1945. Sample size as of 12 months before the layoff: 290.

at or around the end of the war are employed 12 months later. Within that group, almost 80 percent were employed in a different industry. 14.1 percent were jobless and the vast majority of them (10.3 percent out of 14.1 percent) were nonparticipants. Three years later, the share of employed increased further. Accordingly, the share of unemployed decreased and a large portion of those who are out of the labor force one year after the layoff returned to work.

In summary, various pieces of evidence suggest that despite a large reallocation force to which the economy was subject at the time, the response of the labor market was quick and smooth, without causing large involuntary unemployment. In the next section, we discuss macroeconomic forces that allowed the economy to sustain strong labor demand, enabling the quick absorption of the massive labor flows arising from the ending of WWII.

7 Macroeconomic Forces Leading to Job Creation

The previous sections documented the quick transitions accomplished by workers as well as their occupational mobility. However, those outcomes would only be possible in an economy with significant job creation to replace the labor demand formerly generated by defense purchases and conscription. In this section, we discuss the macroeconomic factors behind

Table 11: Reallocation After Displacement $t = 0$ around the End of WWII

	Between $t = -12$ and 12	Between $t = -12$ and 36
Employed	85.9	91.7
% Switchers	79.1	80.8
% Stayers	22.9	19.2
Unemployed	3.8	2.8
Nonparticipant	10.3	5.5

Notes: Sample of those who are laid off between December 1944 and September 1945. Sample size: 290. Industry switches are based on 3-digit level classification.

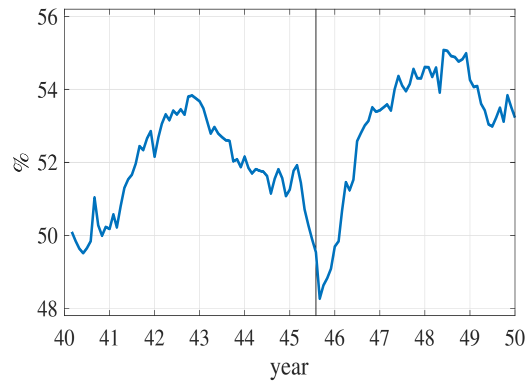
the high level of job creation.

7.1 Macroeconomic Background and Possible Explanations

Numerous contemporary economists, forecasters, and policymakers worried that the economy would fall back into depression and deflation once the war stimulus evaporated. For example, in August 1945, the US Office of War Mobilization and Reconversion predicted that the number of unemployed could rise to 8 million by spring 1946, implying a civilian unemployment rate of over 13 percent. In November 1945, economists from that office used a Keynesian-based econometric model to produce nowcasts of GNP for 1945Q4 that were 11 percent lower than actual GNP.[19] Contrary to the forecasts, the economy experienced a robust recovery, with private demand replacing a large part of the war demand. Moreover, the price level rose by 20 percent in the year and a half after the end of the war. In September 1945, Laurence Klein's new model predicted the robust recovery in GNP, but he did not publicize the results because he thought that the model was too preliminary; he continued to think the economy would return to depression (Bjerkholt (2014), p. 772-773). In his "post-mortem" *JPE* paper, Klein (1946) sought to understand why standard Keynesian-based econometric models were so wrong in their predictions. He concluded that a key mistake was classifying investment as autonomous and not including enough lags. Woytinsky (1947),

[19] See Klein's (1946) discussion of the Hagen-Kirkpatrick forecasts.

Figure 18: Civilian Employment-to-Population Ratio



Note: Employment includes emergency workers, population is ages 14 and over. Seasonally adjusted using X-12.

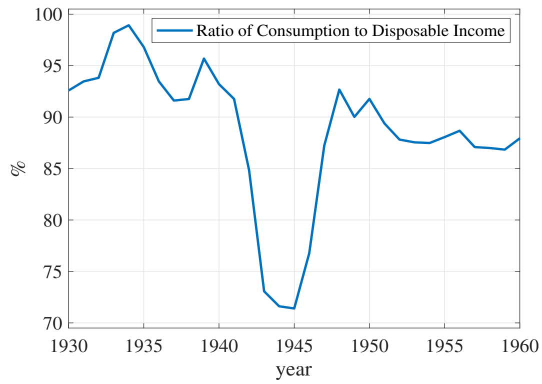
in contrast, argued that the problem lay with the Keynesian consumption function itself.[20]

The strength of the recovery showed up clearly in employment. Figure 18 shows the civilian employment-population ratio, with the New Deal emergency workers before the war counted as employed. The denominator is the population ages 14 and older. The total number employed is a lower bound on the number of civilian jobs available because it does not include vacancies (unfilled jobs); as shown in Figure 2 in a previous section, the vacancy rate remained elevated for several years after the end of WWII. After the temporary dip during winter 1945-46 (discussed earlier in Section 4), the civilian employment-population ratio in the second half of 1946 was three percentage points above the 1940 average. Moreover, it continued to rise another two percentage points through 1948.

A leading explanation for the strong recovery of the economy was the "pent-up demand" hypothesis (e.g. Council of Economic Advisers (1947), Gordon (1952)). This story argued that the shortages and rationing of WWII created pent-up demand for consumer goods. Gordon (1952) (Ch. 14) documented that transfer payments helped prop up disposable income, which could have boosted consumption, but also drew attention to the economic incentives for firms to invest in plant, equipment, inventories, and residential structures and

[20]The lively debate between Klein (1946) and Woytinsky (1946, 1947) on the Keynesian consumption function illustrates the tremendous value of the later breakthroughs by Modigliani and Friedman for understanding consumption behavior.

Figure 19: The Behavior of Consumption During the 1940s



Notes: The data are from the National Income and Product Accounts.

for consumers to replenish their depleted consumer durable stocks.

Accumulated financial assets was an important part of the pent-up demand story. The same shortages and rationing during the war also led to forced saving and the accumulation of financial assets (e.g. war bonds) by households, permitting them to go on a buying spree after the war. There are a few gaps in the accumulated financial asset part of the story, however. First, as Higgs (2012) pointed out, the data show that households did not reduce their holdings of financial assets, and particularly war bonds, in the aggregate. Second, the high inflation that occurred when price controls were lifted significantly reduced the real value of the nominal assets that consumers had accumulated, i.e., the government levied an inflation tax on nominal assets. Figure 19 shows that the ratio of consumption to disposable income plunged during WWII and rose when WWII ended. However, the post-war level did not exceed the pre-war level. This suggests the traditional aggregate demand story may be more complicated than suggested by the traditional explanation for the fast recovery of the U.S. economy.

To our knowledge, there was no discussion in the 1940s or early 1950s of a possible role for accommodative monetary policy in the post-war boom. The Fed kept treasury rates near zero despite the significant rise in prices immediately after the war. (See Figure 9 of Ramey and Zubairy (2018).) The result was an average *ex post* real interest rate of -15 percent in the 18 months after the end of the war. What matters for consumption and investment decisions, though, is the *ex ante* real interest rate, i.e., the nominal interest rate minus *expected* inflation.

What were inflationary expectations in the immediate post-war period? In their analysis of the WWII inflation from 1939 and 1948, Friedman and Schwartz (1980) argued that "almost certainly the most widely-held expectation at the time was that prices would go down after the war—if this expectation seems unreasonable to us, it is only by hindsight" (p. 143). They also maintained that "the public acted from 1946 to 1948 as if it expected deflation" (p. 167). The public expected deflation because of memories of the sharp decline in prices after WWI and memories of the Great Depression along with contemporaneous forecasts of a return to depression and deflation once the wartime stimulus was ended.

The Livingston Survey data (Croushore (1997), which begins in June 1946, is broadly consistent with Friedman and Schwartz's view. Joseph Livingston, a columnist with the Philadelphia Inquirer, began conducting a semi-annual survey of economic expectations in June 1946, though the initial survey asked only the 6-month ahead forecast. The median forecast (calculated from the data that is available at the Federal Reserve Bank of Philadelphia) was a 7 percent rise in prices from June 1946 to December 1946. Inflation over the previous 12 months had been only 3 percent, but the expectation of significant price increases during this period is not surprising because everyone knew that the wartime price controls would be lifted in the summer of 1946. Actual prices rose 15 percent over this six month period, exceeding the forecasts. Despite this large positive forecast error, in December 1946 the median forecast was for a 6 percent *fall* in prices over the next twelve months—respondents were still forecasting deflation! Thus, *ex ante* real interest rates were often significantly positive during the immediate post-war period, despite nominal interest rates being near zero.

Given the gaps in the monetary and financial explanations, we instead highlight the economic incentives discussed by Gordon (1952) by exploring a pent-up demand hypothesis that does not depend on Keynesian consumption functions, liquidity from accumulated financial assets, or monetary accommodation. Our alternative hypothesis is instead based solely on dynamic general equilibrium neoclassical forces. The traditional literature has often pointed to the price controls and rationing as leading to pent-up demand. It must be recognized, however, that even without price controls and rationing, the effects on consumer durable goods and private firm investment and stocks would have been similar since limits to the production capacity of the economy required a crowding out of non-military spending. McGrattan and Ohanian (2010) demonstrate the surprising result that a standard neoclassical model that ignores the price controls and credit constraints can explain the real allocations during WWII quite well when one feeds through exogenous changes in four factors: (i) government spending; (ii) conscription; (iii) government-owned and privately-operated capital; and iv) faster-than-average technology growth.

We extend McGrattan and Ohanian's (2010) analysis to show that the events during the war led to the post-war boom. Specifically, during the war government spending crowded out investment, which exhibits much higher intertemporal elasticities of substitution than nondurables and services consumption. As a result, the levels of the capital stocks at the end of the war were substantially below their steady-state values. When government spending fell, economic incentives led to a surge in private investment that raised capital stocks back to the balanced growth path.

Our story for the post-WWII recovery is a dramatic instance of the forces discussed in recent work by Beraja and Wolf (2021), who argue that the strength of business cycle recoveries depends importantly on whether the previous recession was biased against durable goods. Our story is also related to the work by Erceg and Levin (2006) and McKay and Wieland (2021), who find overshooting of durable spending after recessions that are driven by monetary policy shocks. All three of these papers use New Keynesian models — to allow monetary shocks to have real effects — but the principle mechanism operating through durables stocks is entirely neoclassical. Since all our shocks are real, we use a simple neoclassical social planner model to illustrate our hypothesis.

7.2 A Simple Neoclassical Model of Pent-Up Demand

Our neoclassical model combines a representative household with a representative firm in an economy in which the government must use resources to fight a war. For simplicity, we assume that the government finances the war with lump-sum taxes, so that the competitive equilibrium is identical to the social planner problem. The close match of our model predictions for real allocations to the data suggests that despite the widespread distortions imposed by the U.S. government, such as price and credit controls and command-economy strategies, the macro allocations were similar to what a social planner would choose when forced to fight a war.[21]

A representative household maximizes the present discounted value of utility, given by the following functional form:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \nu \frac{N_t^{1+\phi}}{1+\phi} \right] \tag{7}$$

β is the discount factor and is less than unity. Utility depends on the logarithm of nondurable goods and services consumption, C_t, and a CES function of total hours worked, N_t. Part of consumption services are flows from stocks of residential capital and consumer durable goods. ϕ is the inverse of the Frisch elasticity of labor supply. ν denotes the weight on the disutility of labor. Total hours worked are the sum of hours worked in private production and conscripted hours into the military:

$$N_t = N_t^p + N_t^m. \tag{8}$$

where N_t^P is hours worked in private production and N_t^m is hours worked in the military. The economy's production function is Cobb-Douglas:

$$Y_t^p = \left(u_t K_{t-1}^p + K_{t-1}^g \right)^\alpha \left(Z_t N_t^p \right)^{1-\alpha} \tag{9}$$

[21] Of course, the distribution of income across heterogeneous households and firms would be very different.

Y_t^p is privately produced goods and services. The first term in parenthesis is capital input. u_t is the utilization rate, K_{t-1}^p is the private capital stock (including nonresidential capital, residential capital and consumer durable goods) at the end of period $t-1$, K_{t-1}^g is government-owned, privately-operated (GOPO) stock of capital at the end of period $t-1$, Z_t is labor-augmenting technology, and N_t^p is the quantity of labor used in private production. As Gordon (1969) documented, GOPO capital was a sizable input to aggregate production during and after WWII. Like McGrattan and Ohanian (2010), we assume that GOPO capital is a perfect substitute for private capital in production.

The private capital accumulation equation incorporates both a cost of using the private capital stock more intensively and a capital adjustment cost:

$$K_t^p = (1 - a(u_t))K_{t-1}^p + \Psi\left(\frac{I_t^p}{K_{t-1}^p}\right) \cdot K_{t-1}^p, \tag{10}$$

where $a(u_t)$ is the depreciation rate on private capital, $\Psi(.)$ represents the adjustment cost function, and I_t^p is private investment (again including purchases of consumer durables and residential investment). The depreciation rate $a(u_t)$ is an increasing and convex function of the utilization rate u_t. We assume that $a(u_t)$ takes the following specific form so that u_t is unity in steady state:

$$a(u_t) = \delta + \delta_1(u_t - 1) + \frac{\delta_2}{2}(u_t - 1)^2, \tag{11}$$

where δ is the depreciation rate when utilization is unity, and δ_1 and δ_2 are parameters. The adjustment cost term, $\Psi\left(\frac{I_t^p}{K_{t-1}^p}\right)$, satisfies $\Psi(\delta) = \delta$, $\Psi'(\delta) = 1$, and $\Psi''(\delta) < 1$. We assume the following specific form:

$$\Psi\left(\frac{I_t^p}{K_{t-1}^p}\right) = \delta + \left(\frac{I_t^p}{K_{t-1}^p} - \delta\right) - \frac{\psi}{2}\left(\frac{I_t^p}{K_{t-1}^p} - \delta\right)^2, \tag{12}$$

where ψ is a parameter.

Let G_t^p denote government purchases of private output in period t. Some of these purchases contribute to the accumulation of GOPO, but the bulk are used to purchase tanks, airplanes, etc. We do not explicitly specify the accumulation equation for GOPO capital, since GOPO is chosen exogenously in our model and the other components of G_t^p do not enter utility or production. The resource constraint for private output is:

$$C_t + I_t^p + G_t^p \leq Y_t^p. \tag{13}$$

Total government spending includes both government purchases of privately produced goods (G_t^p) and government-produced goods (G_t^g). The latter specifically corresponds to the production of military services, measured by the compensation of military personnel, which equals the product of wages and hours worked by military personnel N_t^m. We assume that the government pays wages equal to the private production wage. Thus,

$$G_t = G_t^p + G_t^g \text{ where } G_t^g = (1-\alpha)\frac{Y_t^p}{N_t^p} \cdot N_t^m. \tag{14}$$

As discussed earlier, government spending is financed with lump-sum taxation, so

$$G_t = T_t \tag{15}$$

where T_t is lump-sum taxes. In the representative household, perfect financial markets, and rational expectations case, the timing of the lump-sum taxes has no effect: deficit spending with later increases in lump-sum taxes is equivalent to balanced budget lump-sum taxes.

GDP (Y_t) is equal to private production plus government production, with the latter valued by the wage bill for the military:

$$Y_t = C_t + I_t^p + G_t^p + G_t^g = Y_t^p + (1-\alpha)\frac{Y_t^p}{N_t^p} N_t^m. \tag{16}$$

In this economy, the sequences G_t^p, N_t^m, and K_t^g are exogenously determined by war needs. Labor-augmenting technology, Z_t, is also exogenous. The social planner chooses sequences C_t, N_t^P, u_t, I_t^p, Y_t^p, and K_t^p to maximize the lifetime utility of the representative household given in equation (7), subject to the hours constraint (8), the production function (9), the capital accumulation equation (10), and the resource constraint for private output (13).

Table 12: Baseline Calibration of the Model

Parameter	Value	Description (all rates are quarterly)
β	0.985	Subjective discount factor
ν	3.367	Weight on disutility of labor, set so $n = 0.5$ in steady state
ϕ	0.75	Inverse of the Frisch elasticity of labor supply
α	0.33	Exponent on capital input in production function
δ	0.015	Depreciation rate of private capital
g_y	0.15	Steady-state share of total government spending to GDP
η	20	Elasticity of the investment-capital ratio w.r.t. q
δ_1	$\frac{1}{\beta} - 1 + \delta$	Parameter on linear term of capital utilization cost
δ_2	$3 \cdot \delta_1$	Parameter on quadratic term of capital utilization cost
ψ	$\frac{1}{\delta \cdot \eta}$	Capital adjustment cost
γ_n	0.0025	Growth rate of population ages 14+
γ_z	0.0099	Growth rate of labor-augmenting technology

In order to compare the model results with actual data, we allow both labor-augmenting technology Z_t and population to grow along the balanced path. Thus, we must transform the model's variables so that they are constant in steady state. Once we solve for the transformed variables, we multiply the responses by the growth factors.[22] The first-order conditions and steady-state conditions for the model with growth are presented in the appendix.

The calibrated parameters are shown in Table 12. We start with standard values for the post-war period but modify some slightly to match the WWII period. For example, in order to match the relatively high consumption-GDP fraction in 1939 (0.72), we use slightly lower values of the discount factor β, the capital share α, and depreciation rate δ than typically used in papers calibrated to more modern data. The value of the steady-state government spending fraction of GDP is set to the 1939 value of 0.15. The inverse Frisch elasticity, capital adjustment cost parameters, and utilization parameters were set at typical values initially and adjusted to roughly match the patterns in the data.[23]

[22]Several adjustments must be made to the calibration of the utilization cost function and capital adjustment costs to include the growth factor. The appendix gives more detail.

[23]For example, instead of a typical Frisch elasticity of 1, ours is set a little higher to 1.3 since our model does not incorporate patriotic motives for increasing labor supply. The factor in the quadratic term of the utilization cost is typically set slightly above 2, whereas ours is set at 3. The elasticity of investment with respect to Tobin's q is often set to 1 but we set ours to 20 to capture the speedy response of investment observed in the data.

7.3 Model Simulations of Pent-Up Demand

In the second quarter of 1940, news arrives that the U.S. must spend to build up its defense. We choose 1940Q2 as the period when the news arrives since Ramey's (2016) narrative indicates that military events during spring 1940 made policymakers and the public realize that the U.S. would need to start spending significant amounts for defense. Conscription was instituted soon after in September 1940. We use 1940Q1 as the steady state and assume that once the news arrives, agents have perfect foresight about the future paths. This assumption involves far too much foresight relative to reality, but as the simulations will show, the results match the data well nonetheless.[24]

The news causes four exogenous variables to vary from their steady-state growth paths: government spending, the number in the military, government-owned, privately-operated (GOPO) capital, and labor-augmenting technology. We include the exogenous technology change, as do McGrattan and Ohanian (2010), to match the data better though it is not key to our pent-up demand explanation.[25]

The paths of the exogenous variables are shown in Figure 20. The paths of government spending, the number in the military, and government-owned, privately-operated capital are calibrated to actual data through 1947 and then return to their pre-war values a few years later. The path of labor-augmenting technology is calibrated to labor productivity.[26]

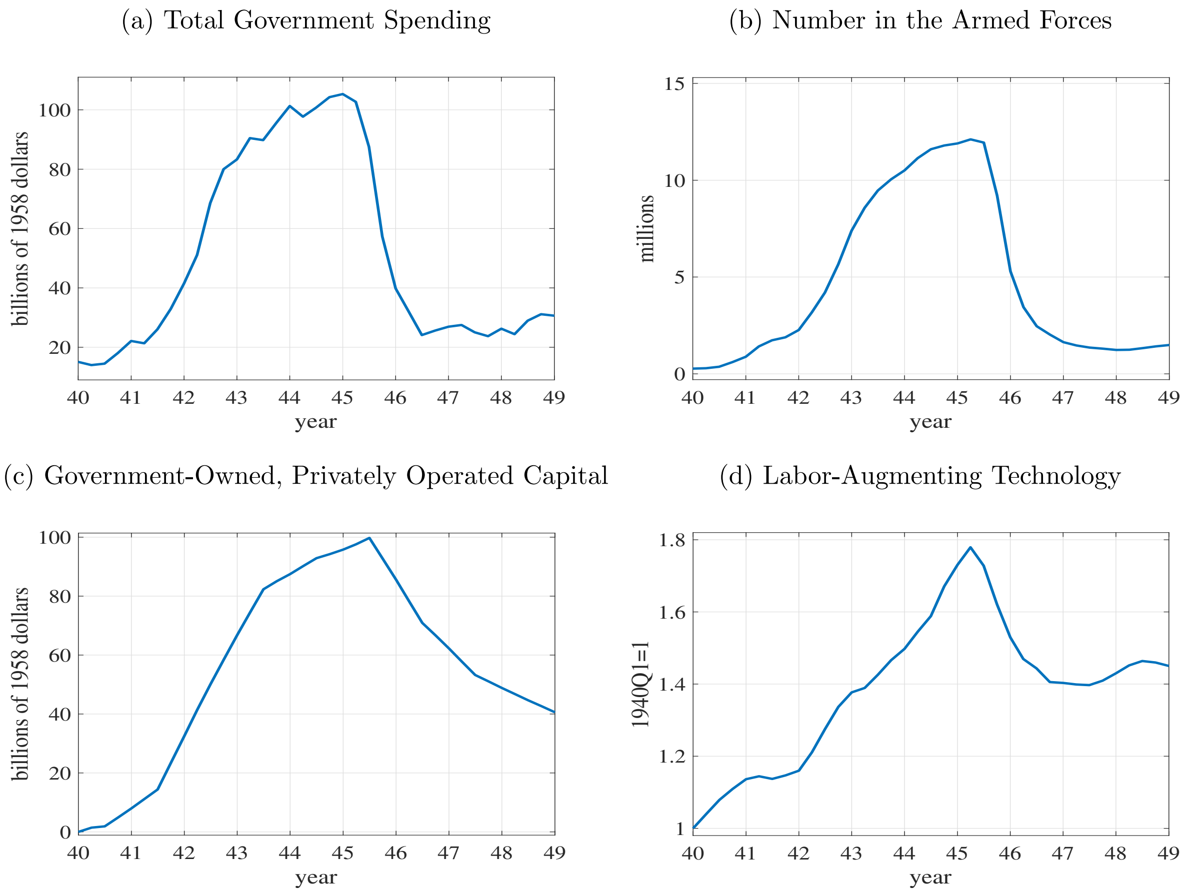
Figure 21 shows the impulse responses from the model simulations versus the behavior of the data. The GDP component data are from Gordon and Krenn (2010) and are in 1958 dollars. For investment, we add Gordon and Krenn's (2010) series on consumer durable purchases to the series on total investment. The consumption series from the data consists

[24]The assumption of foresight of the end of the war is not so far-fetched. After the D-Day invasion of June 1944, government and businesses planned for reconversion because they thought the war in Europe would be won by the end of the year. In contrast, the abrupt end to the war in the Pacific in August 1945 was a surprise.

[25]Since we do not have measures of capital utilization or capital in the data, we adjust the exogenous labor-augmenting technology process so that the model-generated labor technology series, which endogenously depends on the capital stock and utilization, roughly matches the data on labor-augmenting technology. Thus, our matching of the labor productivity series is not an indication of the ability of the model to fit that aspect of the data.

[26]Data details are in the appendix.

Figure 20: Paths of Exogenous Variables



(a) Total Government Spending

(b) Number in the Armed Forces

(c) Government-Owned, Privately Operated Capital

(d) Labor-Augmenting Technology

Notes: the paths are calibrated to actual data through 1947 and are assumed to return to their pre-war values by early 1950.

of nondurables plus services consumption.[27] Finally, the total hours data are from Ramey (2011).

For the WWII period, our quarterly model matches the data well. GDP and hours worked in the model rise as much as in the data. The mechanisms are as follows: The rise in government spending reduces consumption (relative to trend) and raises labor supply through the negative wealth effect. However, conscription, GOPO capital, and the rise in labor-augmenting technology above trend also play a role. Labor productivity increases due to three factors: technological growth, the increase in capital from GOPO, and high capital

[27]The model's consumption measure includes the service flow from the stock of consumer durables. We tried imputing that flow from the stock of consumer durables and adding it to nondurables plus services. It lifted the line almost uniformly, so it didn't improve the fit.

utilization.

Our model produces a fall in consumption relative to trend during the war, but then a large burst after the war, even more than occurred in the actual data. Investment in both the model and the data show a significant U-shape, rising in 1940 through mid-1941, falling significantly in 1942 and staying low through the first part of 1945, and then soaring at the end of the war. Thus, our model can capture the pent-up consumption and investment demand at the end of the war, even without financial market effects.

The model predicts a peak in capital utilization. Recall that the cost of raising capital utilization is faster depreciation of the capital stock. With perfect foresight about the end of the war, the implicit cost of higher depreciation of capital is less than usual, so firms are willing to raise utilization. Unfortunately, we did not have any data on utilization so we cannot compare our model simulation to the data.

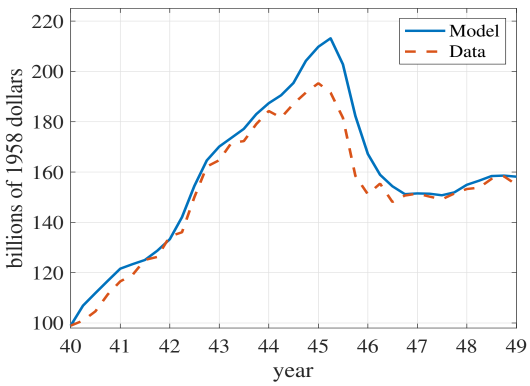
Figure 22 shows the model-generated path of the private capital stock, total capital stock, and total capital input. Recall that total capital input is $uK+K^G$, where u is utilization, K is the private capital stock, and K^G is GOPO capital. The stock of private capital rises briskly through early 1942, but then declines slowly through the end of the war. In contrast, the total capital stock grows faster because of the government's investments in GOPO capital. Total capital *input* rises even more because of higher utilization of capital. After the war, utilization returns to normal but private capital surges.

7.4 Summary of Pent-Up Demand Results

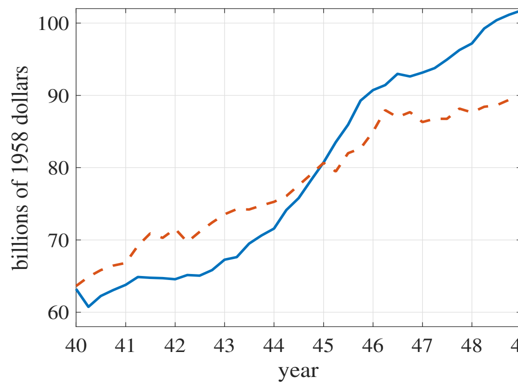
In sum, the crowding out of consumer durable expenditures, residential investment, and business fixed investment during WWII set up incentives for a post-war spending boom. Had government spending crowded out only nondurable goods and services consumption, the recovery would have been much less robust. In actual fact, consumer durable expenditures and much private investment spending were suppressed during WWII by mandates, rationing, and shortages caused by price controls. Nevertheless, the consequences for the capital stocks at the end of the war were the same as they would have been if prices had

Figure 21: Impulse Responses: Model vs. Data

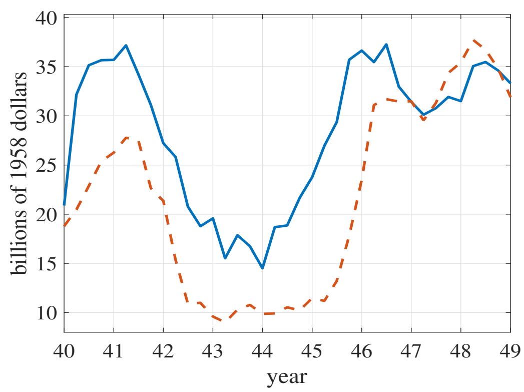
(a) GDP



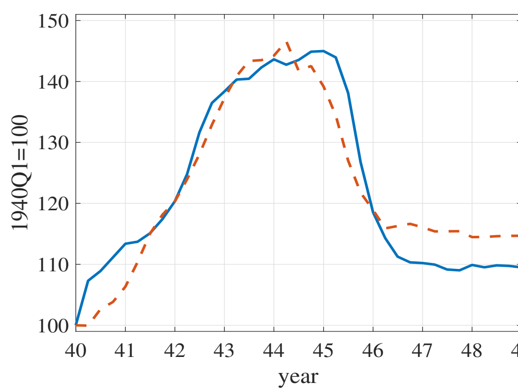
(b) Consumption



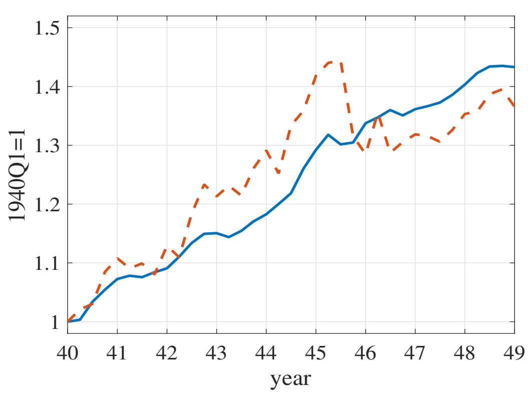
(c) Private Investment



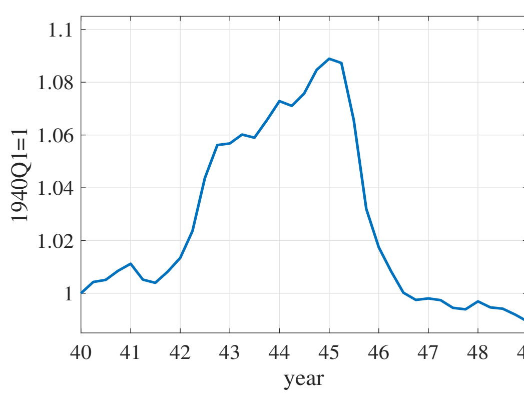
(d) Hours Worked



(e) Labor Productivity

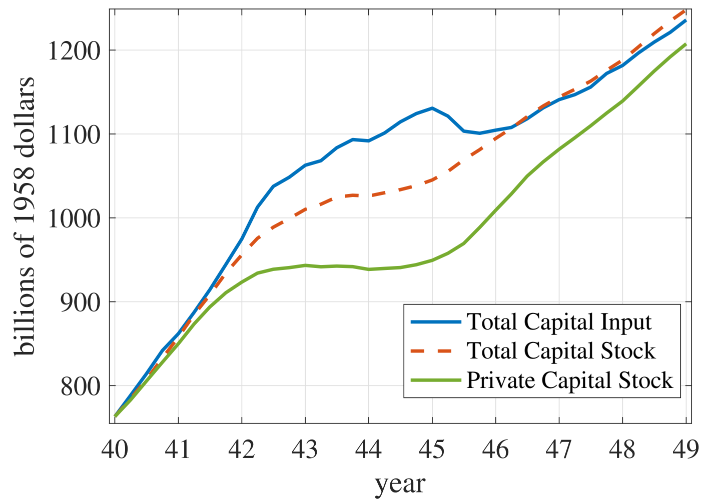


(f) Capital Utilization



Notes: The graphs show the simulations from the model relative to the actual data. The NIPA data are from Gordon and Krenn (2010) and the hours data are from Ramey (2011).

Figure 22: Model Responses: Capital



been allowed to adjust.

We would be remiss not to mention another possible factor that we did not include in our model: the negative real interest rates during that period due to the Federal Reserve's keeping interest rates near zero. The Treasury bill rate varied between 0.38 percent and 1.14 percent from the end of the war through 1948 whereas the rate of inflation averaged 8.5 percent. Thus, real interest rates were significantly negative during the immediate post-war period. We did not see this factor mentioned in contemporary accounts, perhaps because traditional Keynesian models abstracted from monetary factors. However, modern New Keynesian models would predict that this amount of accommodation by the Federal Reserve would exert significant stimulus. We leave a quantitative analysis of this story for further work.

8 Conclusion

In this paper, we have explored the various factors that explain why the U.S. unemployment rate rose so little at the end of WWII. From a Keynesian perspective, one would expect the greatest "fiscal cliff" of the 20th Century to have led to widespread unemployment. From the perspective of the labor market frictions literature, one would also have predicted widespread unemployment. However, the actual behavior of the unemployment rate did not follow these predictions.

The first step in our analysis showed that declines in labor productivity, average hours per worker, and the labor force participation rate were an important factor in dampening the rise in the unemployment rate. However, these factors alone could not explain the small rise in the unemployment rate in light of the large sectoral shifts. We then used our new longitudinal data to document that job-to-job flows were the majority of the gross labor market flows. Our data showed that returning veterans and civilians who lost jobs in war industries quickly transitioned to new jobs. We found these quick transitions despite most flows leading to shifts across industries. Finally, we explored reasons for the robust job creation that allowed workers to find new jobs so quickly. We showed that a version of the "pent-up demand" hypothesis that does not depend on financial market factors or Keynesian amplification can explain the data well. We demonstrated with a modern neoclassical model that the crowding out of consumer durable expenditures and investment expenditures during the war resulted in capital stocks that were far below the balanced growth path. This set the stage for a strong post-war boom in which consumer durables investment, residential investment, and business investment surged.

While the focus of this paper has been on a particular historical period, it generates lessons that are applicable to the 21st Century economy. First, large declines in government spending do not always lead to rises in the unemployment rate. Second, large reallocations of workers across sectors do not always lead to high unemployment rates. Our findings support those of Chodorow-Reich and Wieland's (2020), who find, using data since the 1980s, that sectoral shifts across industries raise the unemployment rate at the local level only during times of national recession, not during national expansions. Thus, Lilien's (1982) famous "sectoral shifts" hypothesis does not appear to apply to a booming economy. Third, periods in which spending on consumer durable goods and investment is temporarily dampened, be it by fiscal crowding out or tight monetary policy, are likely to be followed by vigorous recoveries.

References

Ball, Laurence, Daniel Leigh, and Prakash Loungani. 2017. "Okun's law: Fit at 50?" *Journal of Money, Credit and Banking* 49 (7): 1413–1441.

Beraja, Martin, and Christian K Wolf. 2021. "Demand composition and the strength of recoveries." *NBER Working Paper Series No. 29304*.

Bjerkholt, Olav. 2014. "Lawrence r. klein 1920–2013: Notes on the early years." *Journal of Policy Modeling* 36 (5): 767–784.

Blanchard, Olivier, Alex Domash, and Lawrence Summers. 2022. "Bad news for the fed from the beveridge space." *PIIE Policy Brief* 22 (7): 1–16.

BLS. 1946a. "The labor force in the first year of peace." *Monthly Labor Review* 63 (5): 669–680.

BLS. 1946b. "Trends of employment and labor turn-over." *Monthly Labor Review* 63 (3): 444–464.

Brainard, Lael, and David Cutler. 1993. "Sectoral shifts and cyclical unemployment reconsidered." *Quarterly Journal of Economics* 108 (1): 219–243.

Chodorow-Reich, Gabriel, and Johannes Wieland. 2020. "Secular labor reallocation and business cycles." *Journal of Political Economy* 128 (6): 2245–2287.

Collins, William. 2000. "African-american economic mobility in the 1940s: a portrait from the palmer survey." *Journal of Economic History* 60 (3): 756–781.

Conference, Board. 1941-1942. *Economic Almanac*. National Industrial Conference Board, Inc..

Conference, Board. 1945-1946. *Economic Almanac*. National Industrial Conference Board, Inc..

Croushore, Dean D. 1997. "The livingston survey: Still useful after all these years." *Business Review-Federal Reserve Bank of Philadelphia* 2 1.

Daly, Mary, John Fernald, Òscar Jordà, and Fernanda Nechio. 2013. "Okun's macroscope and the changing cyclicality of underlying margins of adjustment." *Federal Reserve Bank of San Francisco Working Paper 2013-32*.

Daly, Mary, John Fernald, Òscar Jordà, and Fernanda Nechio. 2014. "Interpreting deviations from Okun's law." *FRBSF Economic Letter* (12): .

Daly, Mary, John Fernald, Òscar Jordà, and Fernanda Nechio. 2017. "Shocks and adjustments." *Federal Reserve Bank of San Francisco Working Paper 2013-32*.

Daly, Mary, and Bart Hoijn. 2010. "Okun's law and the unemployment surprise of 2009." *FRBSF Economic Letter* (2010-07): .

Davis, Steven, and Till von Wachter. 2011. "Recessions and the costs of job loss." *Brookings Papers on Economic Activity* Fall 2011 1–55.

Erceg, Christopher, and Andrew Levin. 2006. "Optimal monetary policy with durable consumption goods." *Journal of monetary Economics* 53 (7): 1341–1359.

Feenberg, Daniel, and Jeffrey A Miron. 1997. "Improving the accessibility of the nber's historical data." *Journal of Business & Economic Statistics* 15 (3): 293–299.

Figura, Andrew, and Chris Waller. 2022. "What does the beveridge curve tell us about the likelihood of a soft landing?" *FEDS Notes*.

Friedman, Benjamin M, and Michael L Wachter. 1974. "Unemployment: Okun's law, labor force, and productivity." *Review of Economics and Statistics* 167–176.

Friedman, Milton, and Anna Jacobson Schwartz. 1980. "New deal changes in the banking structure and monetary standard." In *From New Deal Banking Reform to World War II Inflation*, 3–75, Princeton University Press.

Fujita, Shigeru, and Valerie A. Ramey. 2026. "Were women pushed or pulled out of the labor force at the end of wwii?" *in progress.*

Goldin, Claudia. 1991. "The role of World War II in the rise of women's employment." *American Economic Review* 741–756.

Gordon, Robert Aaron. 1952. *Business Fluctuations.* Harper and Brothers.

Gordon, Robert J. 1969. "$45 billion of us private investment has been mislaid." *American Economic Review* 59 (3): 221–238.

Gordon, Robert J, and Robert Krenn. 2010. "The end of the great depression 1939-41: Policy contributions and fiscal multipliers." *NBER Working Paper Series No. 16380.*

Higgs, Robert. 2012. "The myth of pent-up demand and the successful reconversion after World War II." *Foundation for Economic Education Commentary.*

Hubbard, Joseph. 1947. "Reconversion." *Review of Economics and Statistics* 29 (1): 31–38.

Jacobson, Louis, Robert LaLonde, and Daniel Sullivan. 1993. "Earnings losses of displaced workers." *American Economic Review* 83 (4): 685–709.

Klein, Lawrence R. 1946. "A post-mortem on transition predictions of national product." *Journal of Political Economy* 54 (4): 289–308.

Knotek, Edward. 2007. "How useful is Okun's law?" *Federal Reserve Bank of Kansas City Economic Review* Fourth Quarter 73–103.

Lennon, Conor. 2021. "GI Jane goes to college? Female educational attainment, earnings, and the Servicemen's Readjustment Act of 1944." *Journal of Economic History* 81 (4): 1223–1253.

Lilien, David M. 1982. "Sectoral shifts and cyclical unemployment." *Journal of Political economy* 90 (4): 777–793.

McGrattan, Ellen R, and Lee E Ohanian. 2010. "Does neoclassical theory account for the effects of big fiscal shocks? Evidence from World War II." *International Economic Review* 51 (2): 509–532.

McKay, Alisdair, and Johannes F Wieland. 2021. "Lumpy durable consumption demand and the limited ammunition of monetary policy." *Econometrica* 89 (6): 2717–2749.

Meyer, Brent, and Murat Tasci. 2012. "An unstable Okun's law, not the best rule of thumb." *Federal Reserve Bank of Cleveland Economic Commentary* (2012-08): .

Mulligan, Casey B. 1998. "Pecuniary incentives to work in the United States during World War II." *Journal of Political Economy* 106 (5): 1033–1077.

Okun, Arthur M. 1963. "Potential GNP: its measurement and significance (pp. 98-103)." *Yale University, Cowles Foundation for Research in Economics.*

Owyang, Michael, and Tatevik Sekhposyan. 2012. "Okun's law over the business cycle: Was the Great Recession all that different?" *Federal Reserve Bank of St. Louis Review* 95 (4): 399–418.

Palmer, Gladys Louise, and Carol Brainerd. 1954. *Labor Mobility in Six Cities: A Report on the Survey of Patterns and Factors in Labor Mobility, 1940-1950.* New York: Social Science Research Council.

Plosser, Charles I, and G William Schwert. 1979. "Potential gnp: Its measurement and significance: A dissenting opinion." In *Carnegie-Rochester Conference Series on Public Policy*, Volume 10. 179–186, Elsevier.

Prachowny, Martin FJ. 1993. "Okun's law: theoretical foundations and revised estimates." *Review of Economics and Statistics* 331–336.

Ramey, Valerie A. 2011. "Identifying government spending shocks: It's all in the timing." *Quarterly Journal of Economics* 126 (1): 1–50.

Ramey, Valerie A. 2016. "Defense news shocks, 1889-2015: Estimates based on news sources." *working paper.*

Ramey, Valerie, and Sarah Zubairy. 2018. "Government spending multipliers in good times and in bad: Evidence from US historical data." *Journal of Political Economy* 126 (2): 850–901.

Ruggles, Steven, Sarah Flood, Matthew Sobek et al. 2024. , IPUMS USA: Version 15.0 [dataset]. Minneapolis, MN: IPUMS.

Ruhm, Christopher. 1991. "Are workers permanently scarred by job displacements." *American Economic Review* 81 319–23.

Stevens, Ann Huff. 1997. "Persistent effects of job displacement: The importance of multiple job losses." *Journal of Labor Economics* 15 (1): 165–88.

Wasson, Robert, John Musgrave, and Claudia Harkins. 1970. "Alternative estimates of business fixed capital in the United States, 1925-1968." *Survey of Current Business* 50 (4): 18–36.

Woytinsky, Wladimir S. 1947. "What was wrong in forecasts of postwar depression?" *Journal of Political Economy* 55 (2): 142–151.

Woytinsky, WS. 1946. "Relationship between consumers' expenditures, savings, and disposable income." *Review of Economics and Statistics* 28 (1): 1–12.

Zagorsky, Jay. 1998. "Job vacancies in the United States: 1923 to 1994." *Review of Economics and Statistics* 80 (2): 338–345.

Appendix

A Data Sources

A.1 General Data Sources

Figure 1: The government purchases and GDP data are from Ramey and Zubairy (2018). For 1939–46, they used the quarterly nominal GNP series and government purchases series published in *National Income, 1954 Edition: A Supplement to the Survey of Current Business* to interpolate the modern NIPA annual nominal GDP and government purchases series. We then used quarterly averages of the CPI to interpolate the NIPA annual GDP price deflator using the proportional Denton method. They constructed quarterly real GDP and real government purchases to use as a second-round interpolator of annual NIPA real GDP and government purchases. Both series are divided by potential GDP, which is estimated using a sixth-degree polynomial trend of log real GDP on a sample from 1889 to 2015, excluding 1930-1946.

Figure 2: The unemployment rate series including emergency workers is constructing by splicing the NBER Macrohistory data series m08292a (downloaded from FRED) to the rate created from the official *Current Population Reports* data starting in March 1940. The emergency workers series is from the 1941-42 and 1945-46 volumes of the *Economic Almanac* of the Conference Board (Conference (1941-1942, 1945-1946). The vacancy series are from Zagorsky (1998). We seasonally adjust the series using X-12.

Figure 3: The manufacturing turnover data are from the NBER Macro History Database, series m08254b, m08255b, m08252b, m08251b, which are based on BLS data. We seasonally adjust the series using X-12.

Figure 4 is based on calculations using our new panel dataset based on Palmer and Brainerd (1954).

Figure 5: The military share of employment is based on our Palmer panel and the *Current Population Reports*. The CPR-based discharges are estimated from the change in the population of veterans. Once the war ended, enlistments were minuscule compared to discharges so the change in the population of veterans is a good approximation to discharges after August 1945.

Figure 9: Raw data are from the U.S. Bureau of the Census, *Current Population Reports*, Series P-50, No. 2. The monthly data first became available in March 1940. The variables are seasonally adjusted using X-12.

Figure 10: Raw data are from the U.S. Bureau of the Census, *Current Population Reports*, Series P-50, No. 13 and later. The data are not seasonally adjusted.

Figure **??**: Civilian unemployment rates calculated from the U.S. Census Bureau *Current Population Reports*, Series P-50, No. 2. The series are seasonally adjusted using X-12.

Figure 18: Raw data are from the U.S. Bureau of the Census, *Current Population Reports*, Series P-50, No. 2. The civilian employment count is augmented by data on emergency workers from the 1941-42 and 1945-46 volumes of the *Economic Almanac* of the Conference

Board (Conference (1941-1942, 1945-1946). Population is the civilian population ages 14 and over. The series is seasonally adjusted using X12.

Figure 19: Nominal consumption expenditures and disposable income are from the National Income and Product Accounts, annual data downloaded from FRED.

Figure 20 and Figure 21: All GDP components are from Gordon and Krenn (2010) and are in 1958 dollars. The number in the armed forces is from the *Current Population Reports*, the fraction of GOPO capital relative to business nonresidential capital is calculated from Wasson et al. (1970) Tables 1 and 7 and then adjusted relative to total capital using modern BEA tables, and labor-augmenting technology is based on smoothing labor productivity, constructed as Gordon and Krenn's (2010) real GDP series divided by Ramey's (2011) total hours series.

A.2 Data Sources and Construction for Okun's Law Analysis

The Okun's law analysis in Section 4 uses the following series: (i) real GDP, (ii) labor productivity (measured by real GDP per hour, (iii) the labor force participation rate, (iv) the unemployment rate, and (v) weekly hours per worker. The sample period for these series is 1940Q1-2024Q1. Each variable for this period is constructed as follows.

(i) Real GDP. For the period 1940Q1-1946Q4, we use real GDP constructed by Ramey and Zubairy (2018). For the period from 1947Q1, we use the current vintage of the GDP series as of July 2024, available directly from the Bureau of Economic Analysis website. We splice the two series multiplicatively using the ratio of the average values for the period between 1947Q1-1947Q4 for which two series overlap.

(ii) Labor productivity. We construct the series by dividing real GDP by aggregate hours. The construction of the GDP series is discussed above. Aggregate hours cover the total economy including armed forces. For the period between 1940Q and 1947Q4, we use the aggregate hours series constructed by Ramey and Zubairy (2018). For the remaining period, the aggregate hours series that includes the armed forces is available from the Bureau of Labor Statistics (BLS), Office of Productivity and Technology as "Total U.S. economy: hours and employment" available at https://www.bls.gov/productivity/tables/total-economy-hours-employment.xlsx. We express each of the two productivity series as an index that takes 1 in 1948Q1 and then splice them together.

(iii) The labor force participation rate. For the period between 1940 and 1947, we collected 14+ civilian population, civilian labor force, and the size of the armed forces from various issues of the Census Department's *Current Population Reports*.. The participation rate then is calculated by adding the armed forces to the civilian labor force and 14+ population and taking the ratio of the two. From 1948Q1 on, the labor force participation rate is readily available from the BLS's Current Population Survey but covers only civilians. We make an adjustment to this series that incorporates the armed forces. The size of the armed forces is available from the BLS dataset discussed in (ii) above. We add military personnel to both the numerator and the denominator. We make no adjustment to the age coverage (14+ vs. 16+) of the population series. We splice the two series multiplicatively using the ratio of the average values for the period between 1948Q1-1948Q4 where the two series overlap.

(iv) The unemployment rate. For the period between 1940 and 1947, we use the data collected from the various issues of the Census Department's *Current Population Reports*, namely, the civilian labor force, the armed forces, the number of unemployed, and the number of emergency workers are all available from the same sources. We add the armed forces to the civilian labor force to obtain the total labor force. Note that the reported number of unemployed includes emergency workers. We count them toward employed and calculate the adjusted number of unemployed as a ratio of the total labor force. From 1948 on, the data on the number of unemployed and the civilian labor force are readily available from the BLS's Current Population Survey. We add the armed forces to the civilian labor force to obtain the total labor force. The unemployment rate is calculated as the number of unemployed divided by the total labor force. Again, the size of the armed forces is available from the data discussed in (ii) above.

(v) Average weekly hours. The data for March 1943 through 1947 are from the Census *Current Population Reports*, P-50, no. 13, Table 11. These are average hours for civilian persons at work. To create a consistent series for June 1941 through February 1943, we use FRED NBER Macrohistory series M08304USM310NNBR for average hours per worker in non-agriculture, along with information from the Census' *Monthly Labor Force Bulletin* and *Current Population Reports* to create a series for all civilian workers. For January 1940 through May 1941, we use growth in the NBER Macrohistory series for average hours in manufacturing to project our series back. Starting in 1948Q1, the BLS dataset discussed in (ii) contains the series on aggregate hours and employment for total economy (including the armed forces), from which we calculate weekly hours. The level difference at the seam is adjusted multiplicatively by using the ratio of the average values for the one-year overlapping period.

Note that the labor market data for the 1940s discussed above are reported as non-seasonally adjusted data. We seasonally-adjust them by using the Census X12 software with a default setting. To run the raw series through the X12 routine, we extend the underlying data through 1964 from the same consistent source (Survey of Current Business). We then use those seasonally-adjusted data through the late 1940s as described above.

B Neoclassical Model Details

This section provides the equations of the model with population and technology growth, along with the first-order conditions and steady-state conditions. We assume that population grows at deterministic rate γ_{pop}. Labor-augmenting technology Z_t fluctuates around a deterministic path that grows at γ_z per period. To solve the model, we first transform all variables into stationary variables that are constant in the steady state. After solving the transformed model, we multiply the deterministic growth rates of population and technology to obtain the paths of the aggregate variables that can be compared to the actual data.

Lowercase letters represent per capita versions of the aggregate variables in the model described in the main text, e.g., hours per capita are given by $n_t = \frac{N_t}{Pop_t}$. Variables that are also divided by the deterministic component of technology $(1+\gamma_z)^t$ are denoted by lowercase letters with hats, e.g., $\hat{c}_t = \frac{C_t}{Pop_t \cdot (1+\gamma_z)^t}$. The variables divided by its deterministic growth path of technology are represented by lowercase letters with tilde, e.g., $\tilde{z}_t$.

A representative household maximizes the present discounted value of utility:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln \hat{c}_t - \nu_t \frac{n_t^{1+\phi}}{1+\phi} \right]. \tag{A.1}$$

Total hours worked are the sum of hours worked in private production and conscripted hours into the military:

$$n_t = n_t^p + n_t^m, \tag{A.2}$$

The detrended version of the production fuction is:

$$\hat{y}_t^p = \left(u_t \hat{k}_{t-1}^p + \hat{k}_{t-1}^g \right)^{\alpha} \left(\tilde{z}_t n_t^p \right)^{1-\alpha}. \tag{A.3}$$

Note that k_{t-1}^p is the privately-owned capital stock at the end of period $t-1$ detrended by population and the deterministic component of technology in period t. The same timing convention applies to k_{t-1}^g.

The capital accumulation equation must be modified relative to the one shown in the main text because of the switch to normalized variables to account for the growth of both population and technology. The capital accumulation equation is now:

$$\Gamma \hat{k}_t^p = (1 - a(u_t)) \hat{k}_{t-1}^p + \Psi \left(\frac{\hat{i}_t^p}{\hat{k}_{t-1}^p} \right) \cdot \hat{k}_{t-1}^p, \tag{A.4}$$

where $\Gamma = (1+\gamma_{pop})(1+\gamma_z)$ is the factor accounting for growth of population and technology that emerges when one divides both sides of the original capital accumulation equation by population and technology. The form of $a(u_t)$ is adjusted from the main text to take account of growth. To ensure u_t equals unity in a steady state, we use the following modified functional form:

$$a(u_t) = \delta + \delta_1'(u_t - 1) + \frac{\delta_2'}{2}(u_t - 1)^2, \tag{A.5}$$

where $\delta_1' = \delta + \frac{\Gamma}{\beta} - 1$, and δ_2' is proportional to δ_1'.

Similarly, the functional form of the adjustment cost term need to be modified as follows:

$$\Psi\left(\frac{\hat{i}_t^p}{\hat{k}_{t-1}^p}\right) = \delta + \Gamma - 1 + \left(\frac{\hat{i}_t^p}{\hat{k}_{t-1}^p} - \delta - \Gamma + 1\right) - \frac{\psi}{2}\left(\frac{\hat{i}_t^p}{\hat{k}_{t-1}^p} - \delta - \Gamma + 1\right)^2. \tag{A.6}$$

The resource constraint for private output is:

$$\hat{c}_t + \hat{i}_t^p + \hat{g}_t^p = \hat{y}_t^p. \tag{A.7}$$

As noted in the main text, total government spending consists of government purchases of private goods (g_t) plus the compensation of military personnel:

$$\hat{g}_t = \hat{g}_t^p + (1-\alpha)\frac{\hat{y}_t^p}{n_t^p} \cdot n_t^m. \tag{A.8}$$

The government budget constraint is:

$$\hat{g}_t = \hat{t}_t. \tag{A.9}$$

The accounting equation for GDP is:

$$\hat{y}_t = \hat{y}_t^p + (1-\alpha)\frac{\hat{y}_t^p}{n_t^p} \cdot n_t^m. \tag{A.10}$$

In this economy, the social planner chooses sequences $\{\hat{c}_t\}$, $\{n_t^P\}$, $\{u_t\}$, $\{\hat{i}_t\}$, $\{\hat{y}_t^p\}$, and $\{\hat{k}_t^P\}$ to maximize the lifetime utility of the representative household given in Equation (A.1), subject to the hours constraint (A.2), the production function (A.3), the capital accumulation equation (A.4), and the resource constraint (A.7), under the exogenous sequences of $\{\hat{g}_t^p\}, \{n_t^m\}, \{\hat{k}_t^p\}, \{\tilde{z}_t\},$ and $\{\nu_t\}$.

Since there are no distortions, the social planner problem gives the same allocation as the competitive equilibrium. The Lagrangian for the social planner problem is:

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ \ln \hat{c}_t - \nu_t \frac{n_t^{1+\phi}}{1+\phi} + \lambda_t \left[\left(u_t \hat{k}_{t-1}^p + \hat{k}_{t-1}^g\right)^\alpha (\tilde{z}_t n_t^p)^{1-\alpha} - \hat{c}_t - \hat{i}_t^p - \hat{g}_t^p\right]$$
$$+ q_t \lambda_t \left[(1-a(u_t))\hat{k}_{t-1}^p + \Psi\left(\frac{\hat{i}_t^p}{\hat{k}_{t-1}^p}\right)\hat{k}_{t-1}^p - \Gamma \hat{k}_t^p\right]\Bigg\},$$

where λ_t is the Lagrange multiplier and q_t is Brainard-Tobin's q.

The first-order conditions for (in order) $\hat{c}_t$, n_t^p, u_t, $\hat{i}_t^p$, and $\hat{k}_t^p$ are, respectively:

$$\frac{1}{\hat{c}_t} = \lambda_t,$$

$$\nu_t n_t^\phi = (1-\alpha)\lambda_t \frac{\hat{y}_t^p}{n_t^p}$$

$$\frac{\alpha \hat{y}_t}{u_t \hat{k}^p_{t-1} + \hat{k}^g_{t-1}} = q_t a'(u_t),$$

$$\frac{1}{q_t} = \Psi'\left(\frac{\hat{i}^p_t}{\hat{k}^p_{t-1}}\right),$$

$$\Gamma \lambda_t q_t = \beta E_t \lambda_{t+1} \left\{ \frac{\alpha u_{t+1} \hat{y}^p_{t+1}}{u_{t+1}\hat{k}^p_t + \hat{k}^g_t} + q_{t+1}\left[1 - a(u_{t+1}) + \Psi\left(\frac{\hat{i}^p_{t+1}}{\hat{k}^p_t}\right) - \Psi'\left(\frac{\hat{i}^p_{t+1}}{\hat{k}^p_t}\right)\frac{\hat{i}^p_{t+1}}{\hat{k}^p_t}\right]\right\},$$

where

$$a'(u_t) = \delta'_1 + \delta'_2(u_t - 1),$$

and

$$\Psi'\left(\frac{\hat{i}^p_t}{\hat{k}^p_{t-1}}\right) = 1 - \psi \cdot \left(\frac{\hat{i}^p_t}{\hat{k}^p_{t-1}} - \delta - \Gamma + 1\right).$$

The equations for the steady state in the transformed variables, assuming $\hat{k}^g = n^m = 0$, $\tilde{z} = 1$, $q = 1$, and $u = 1$ are:

$$\begin{aligned}
n^{\phi+1} &= \frac{(1-\alpha)}{\nu} \cdot \frac{\hat{y}^p}{\hat{c}}, \\
\hat{y}^p &= (\hat{k}^p)^\alpha (\hat{n}^p)^{1-\alpha}, \\
\hat{i}^p &= (\delta + \Gamma - 1)\hat{k}^p, \\
\frac{\hat{k}^p}{\hat{y}^p} &= \frac{\alpha}{\frac{\Gamma}{\beta} - 1 + \delta}, \\
\hat{y}^p &= \hat{c} + \hat{i}^p + \hat{g}^p.
\end{aligned}$$

We can solve these five equations for five unknowns: $\hat{y}^p, \hat{k}^p, n_p, \hat{i}^p,$ and $\hat{c}$.

The paths of untransformed variables can be found by multiplying the paths of the stationary variables by the growth factors, e.g., $Y^p_t = \hat{y}^p_t \Gamma^t$.