

# War Mobilization and Economic Development: World War II and Structural Transformation in India \*

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## Abstract

Can temporary wartime mobilization change the long-run development trajectory of an economy? We study how mobilization for World War II in colonial India influenced its subsequent long-run economic development. From 1939 to 1945, the British colonial government purchased massive amounts of war materiel within India. We study long-run impacts on Indian structural transformation – the transition of employment from agriculture to the modern sectors (industry and services) – in Indian districts. Causal identification takes a shift-share approach, exploiting variation across industries in war-related government orders, and variation across districts in their pre-war industrial structure. We find that World War II economic mobilization (procurement of war materiel) had a positive and significant impact on long-run structural transformation in Indian districts. More than six decades later, Indian districts that experienced higher procurement of World War II materiel experienced higher structural transformation from agriculture towards industry and services. We find substantial spillovers on services sectors that were not directly subject to World-War-II-related procurement. The majority of structural transformation effects are driven by procurement of heavy industrial goods.

*JEL codes:* H56, N15, N45, O14, O25.

*Keywords:* industrial policy, growth, structural transformation, war mobilization, India

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# 1 Introduction

September 1, 1939 is one of the most famous dates in the 20th century, marking the German invasion of Poland and the start of World War II in Europe. The date two days later is less well-known. On September 3, 1939, the British Viceroy of India, Lord Linlithgow, made a brief address on All India Radio announcing that India was at war with Germany. The British brought India into World War II on the Allied side by fiat, without consulting Gandhi, Nehru, or any other Indian political leader ([Raghavan, 2017](#)). It could do so because India was a British colony, and would remain so until August 15, 1947 (another famous date in history).

India would subsequently make major contributions to Britain's World War II effort. From 1939 to 1945, India served as a major arsenal and war materiel supplier for the British Empire in its war efforts worldwide. The total value of goods procured was phenomenal, amounting to one-sixth of India's pre-war (1938) GDP. This wartime procurement constituted the last major intervention of the British Raj in the Indian economy ([Sinha and Khera, 1962](#)).

Can temporary war mobilization change the long-run development trajectory of an economy? We study how the economic mobilization of colonial India for World War II – its supply of materiel for the war effort – influenced independent India's subsequent long-run economic development. We are interested in structural transformation (the transition of employment from agriculture to industry and services) in Indian districts that were exposed to varying degrees of World-War-II-related demand for war materiel.

For causal identification, we exploit variation across industries in the magnitude of World War II purchases in India by the British colonial government, combined with variation across Indian districts in the pre-war presence of industries producing those war-related products. We combine these sources of variation in a shift-share research design. Our analysis traces the dynamics of effects on structural transformation over nine decades, from 1921 to 2011.

This study is made possible by two innovations on the data front. First, we make use of a unique tabulation of procurement of World War II materiel in India by the British colonial government, which provides the total Indian rupee value of hundreds of distinct procured products. To our knowledge, this data source, [Aggarwal \(1947\)](#), has not previously been used in research in economics. Second, we have made

substantial investments in digitizing district economic structure data from Indian Censuses from 1921 to 1981, which previously were not available in electronic form. With district-level employment at the detailed occupation level from the Census and product-level war procurement from [Aggarwal \(1947\)](#), we can construct our key right-hand-side shift-share variable. The Census data also provide our main dependent variable, structural transformation of the economy from agriculture to the modern (industry and service) sectors.

We find that demand for war materiel during World War II had a positive and statistically significant impact on long-run structural transformation in Indian districts. More than six decades later (through 2011), Indian districts more exposed to World War II procurement see greater transitions of their labor forces from agriculture to the industry and service sectors. The impact of a one-standard-deviation increase in World War II orders per worker leads districts to have approximately 6 percentage points higher share of workers in the modern sectors (roughly one-third standard deviation of the outcome variable). The effect shows up very soon after World War II, by 1951, and persists for six decades, through 2011, with roughly the same magnitude.

Impacts are not limited to the specific industrial sectors that produced war-related goods. In particular, we find substantial spillovers of impacts to service sectors that were not directly subject to the World-War-II-related procurement. Growth of service-sector employment accounts for the majority of structural transformation effects, in both the short and longer run. Employment in “consumer” services (whose demand comes from consumers and households, e.g., personal services and retail trade) shows the largest response to war orders across services subsectors. These patterns are highly suggestive of coordination externalities, such as spillovers to other industries via increases in worker purchasing power ([Murphy et al., 1989](#)).

We also examine impacts of different types of war orders, in particular procurement in light versus heavy industry. We find that the majority of effects on structural transformation are driven by procurement in heavy industrial goods (which includes vehicles, munitions, and chemicals). This finding may reflect the importance of information externalities as a mechanism, for example learning-by doing effects ([Arrow, 1962](#)) and knowledge spillovers across firms ([Hausmann and Rodrik, 2003](#)). Heavy industrial goods were further away from India’s initial comparative advantage at the time of World War II, accounting for only a small minority of industrial employment

(compared to light industrial sectors such as textiles and footwear). The fact that effects are driven by heavy industry procurement points strongly towards positive externalities due to learning-by-doing and learning spillovers across firms.

We address potential threats to causal identification. A pre-trend analysis from 1921-1931 establishes that districts experiencing higher World-War-II-related demand (as measured by our shift-share variable) were not already experiencing more rapid structural transformation in the pre-war period. We also show that our estimates are robust to controlling for time trends that are related to a wide range of baseline (pre-World-War-II) characteristics of districts (economic characteristics, historical conditions, and geographic features). In addition, we also show that variation across districts in military service of soldiers in the war is not driving the empirical results. Our estimates are highly robust to controlling for proxies for a district's population in World War II military service, suggesting that military service in the war effort does not contribute to the structural transformation effects we document.

Our work contributes to three research areas: the economic impacts of war mobilization, the economics of industrial policy, and the long-run consequences of British colonial policies in India.

### *Economic Impacts of Wartime Mobilization*

We contribute to research on the economic consequences of wartime mobilization. Prior research on the impacts of war production and investment, mostly on the U.S., has found mixed results. Many studies argue that World-War-II-related demand had limited impact on post-war productivity growth ([Rhode, 2003](#); [Fishback and Cullen, 2013](#)), for example due to inefficiencies from shifting between civil and military production ([Higgs, 2004](#); [Field, 2008](#); [Rockoff, 2012](#); [Jaworski, 2017](#); [Field, 2022](#)).

Other studies have documented positive effects of military spending and investment on both short- and long-run economic outcomes. Several studies find that World War II military spending had positive effects on productivity through the 1950s, owing to economies of scale, learning by doing, public R&D, and government provisioning of plant and equipment ([Gordon, 1967](#); [Ruttan, 2006](#); [Ristuccia and Tooze, 2013](#); [Gordon, 2017](#)); [Rose \(2018\)](#) and [Bose et al. \(2022\)](#) study impacts on female labor force participation. Similar short-run effects have been noted in Japan, South Korea, and Taiwan during the Vietnam War ([Naya, 1971](#); [Stubbs, 1999](#)). [Moretti et al. \(2021\)](#) find, among OECD countries in recent decades, that government defense-related R&D expenditures have positive spillovers on R&D and productivity growth in the private

sector. Studies have also identified longer-run impacts of war mobilization. [Garin and Rothbaum \(2022\)](#) find that government investment in plants for World War II production had long-run positive effects on overall employment and high-wage manufacturing work in U.S. localities. U.S. public R&D investments in World War II have also been found to have long-run positive effects on patenting and high-tech employment in U.S. localities ([Gross and Sampat, 2023](#)).<sup>1</sup>

Historians have also argued that World War II stimulated subsequent Indian industrialization ([Morris, 1983](#); [Roy, 2016](#)), although there are views to the contrary ([Tomlinson, 1996](#); [Kamtekar, 2002](#)). [McNeill \(1982\)](#) (p. 356) also views World War II production as having given “special impetus to Indian industrialization”.

We contribute with economic analysis of the impact of war mobilization in a context, India, that is more relevant for developing countries overall than prior research focusing on the U.S. or the OECD. Our work is also distinguished in its analysis of very long-run effects of war mobilization – over six decades since World War II.

### *Economics of Industrial Policy*

Our research also sheds light on the impacts of industrial policy (policies aimed at changing the industrial structure of the economy). Wartime mobilization policies are a type of industrial policy, in that they aim to shift production towards industries that contribute to military capability. Since the beginnings of development economics, scholars have highlighted the potential for industrial policy to promote structural transformation from agriculture to industry ([Rosenstein-Rodan, 1943](#); [Nurkse, 1953](#); [Hirschman, 1961](#)). Industrial policy has been seen by many scholars as a key driver of economic development in a number of East Asian countries, such as South Korea and Taiwan ([Amsden, 1989](#); [Wade, 1990](#); [Evans, 1995](#); [Rodrik, 1995](#)). Others have argued that industrial policy has been ineffective or even harmful for economic development ([Baldwin, 1969](#); [Krueger, 1990](#); [Weinstein, 1995](#); [Beason and Weinstein, 1996](#); [Lee, 1996](#); [Pack, 2000](#); [Lederman and Maloney, 2012](#)).

Justifications for industrial policy (as opposed to *laissez-faire*) point to a variety of market failures, such as information imperfections and the need for learning-by-doing ([Arrow, 1962](#); [Hausmann and Rodrik, 2003](#)), coordination externalities ([Buera et al., 2021](#)), and labor-training externalities ([Rodrik, 2007](#)). In many models of

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<sup>1</sup>Relatedly, [Bianchi and Giorcelli \(2023\)](#) show that U.S. Marshall Plan aid had long-run effects on the development of Italian provinces. Studies in political science argue that war is conducive to long-run growth by fostering state-building and institutional development ([Rasler and Thompson \(1985\)](#), [Stubbs \(1999\)](#), [Gupta et al. \(2016\)](#), [Dincecco et al. \(2022\)](#)).

economic growth, there can be low- and high-development equilibria, for example due to financial market incompleteness (Townsend, 1979; Greenwood and Jovanovic, 1990; Bencivenga and Smith, 1991; Acemoglu and Zilibotti, 1997), aggregate demand externalities (Murphy et al., 1989), or credit constraints on human capital investments (Galor and Zeira, 1993). In such growth models, industrial policy can move the economy from a low to a high equilibrium.

We contribute to an emerging literature that exploits historical natural experiments to understand the impacts of industrial policy. Recent such papers include empirical analyses of the South Korean 1970s heavy and chemical industry drive (Liu, 2019; Choi and Levchenko, 2021; Kim et al., 2021; Lane, forthcoming), Finnish World War II reparations (Mitrinen, forthcoming), import trade protection in France (Juhász, 2018), temporary input cost advantages in British shipbuilding (Hanlon, 2020), and China’s 19th-century self-strengthening movement (Bo et al., 2023).<sup>2</sup>

Compared to the literature examining historical episodes of industrial policy, our work is distinguished, first of all, by its geographic scope covering (nearly) all of India, and thus roughly one-sixth of world population. The Indian context, while distinct in its own ways, provides insights that may be of greater relevance to developing countries more broadly than existing research on historical industrial policy episodes in South Korea, Finland, France, or Britain.<sup>3</sup> The impacts of industrial policy may vary across countries with different initial levels of industrialization. The nature of such heterogeneity is ambiguous in theory; industrial policy could have either larger or smaller effects on subsequent development in initially less-developed places.

Our research also takes a very long-run scope compared to most prior studies, over six decades from World War II to 2011. Only Juhász (2018) examines effects of industrial policy over such a long time span (over seven decades in the 19th century). In the analysis of Bo et al. (2023), the end of the 19th century intervention period to 1937 spans roughly four decades. Choi and Levchenko (2021), Mitrinen (forthcom-

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<sup>2</sup>Our work is also related to research using frontier econometric techniques to study modern-era industrial policies, as opposed to policies enacted in a distant historical period (such as Nunn and Trefler (2010), Aghion et al. (2015), Alder et al. (2016), Rotemberg (2019), Criscuolo et al. (2019), Fan (2021), Manelici and Pantea (2021), Giorcelli and Li (2021), Cox (2023)), as well as those using structural estimation (Kalouptsidi, 2018; Barwick et al., 2019). Earlier calibration-based analyses include Head (1994) and Irwin (2000). Harrison and Rodríguez-Clare (2010) provide a literature review. Also related is Kline and Moretti (2014), who study long-run structural transformation due to the U.S. Tennessee Valley Authority’s public infrastructural investments. Dell and Olken (2020) on the persistent impacts of the colonial Dutch cultivation system in Java also has elements in common with the industrial policy literature, in highlighting how historical production investments can affect long-run structural transformation.

<sup>3</sup>Among prior historical studies, only Bo et al. (2023) examines a developing-country context – China – and it does not document effects persisting to the present day.

ing), and [Hanlon \(2020\)](#) examine impacts over roughly 20-30 years from their policy of interest to the final period of analysis.

Finally, our study differs from prior work in the specific form the industrial policy takes. In the Indian World War II context, industrial policy was likely to have operated mainly via government procurement, raising the level of demand faced by producers. By contrast, the industrial policies studied in prior work are credit subsidies (South Korea), trade protection (France), input cost advantages (Britain), and government establishment of factories (China).

### *British Colonialism in Indian Economic History*

Finally, we contribute novel insights in the literature on the long-run impacts of British colonialism in India. Prior work examines the impacts of direct vs. indirect colonial rule ([Banerjee et al. \(2005\)](#), [Iyer \(2010\)](#)), colonial institutions ([Banerjee and Iyer \(2005\)](#), [Gupta et al. \(2016\)](#), [Castelló-Climent et al. \(2018\)](#), [Lee \(2019\)](#)), railroad infrastructure ([Donaldson \(2018\)](#), [Chaudhary and Fenske \(2022\)](#)), and the India-Pakistan partition ([Bharadwaj and Fenske \(2012\)](#), [Bharadwaj et al. \(2015\)](#), [Bharadwaj and Mirza \(2019\)](#)). [Bonfatti and Brey \(2023\)](#) study how reductions in imports due to World War I trade disruptions affect industrialization and support for the anti-colonial movement in Indian districts.

In this context, our work is unique in examining the impacts of war mobilization on long-run economic development. No prior research in Indian economic history has covered this ground.

Our paper is structured as follows. We first provide an overview of World War II mobilization in India. Following that, we describe our empirical analyses, data, and results. We conclude by discussing the implications of our results for economic policy-making and potential future research directions.

## **2 World War II Mobilization in India**

With the onset of World War II, the British colonial government of India initiated a wide-ranging set of policies to expand Indian production of goods needed for the war effort ([Aggarwal, 1947](#); [Sinha and Khera, 1962](#)). Most prominently, war-related public procurement was massive: the total value of goods procured over 1939-1946 amounted

to 17% of 1938 Indian GDP.<sup>4</sup> The vast majority of these World-War-II-related goods were shipped outside India's borders to the other theatres of war. ([Sinha and Khera \(1962\)](#), Appendix Tables 2 and 4).

The government procured goods for the war effort from a wide variety of industries in India, to varying degrees. Our empirical analyses take advantage of this variation in the magnitude of procurement across industries, and the geographic variation in the location of pre-war industries (described below in Section 3).

In addition, the set of government policies to support the war effort included measures such as credit subsidies, subsidies for capital investments, and direct establishment of state-owned firms in key industries. In some cases (such as munitions and machine tools), the government mandated production by private firms, coordinated production across firms (say, to ensure supplies of intermediate inputs), and facilitated knowledge transfer (e.g., via technical assistance missions by foreign experts). The government also supported research institutes to develop substitutes using local materials for goods that were scarce due to war-related trade disruptions.<sup>5</sup>

We would expect that the extent of these other policies to stimulate production in different industries would be highly correlated with the amount of government procurement across industries. The amount of government procurement in an industry can thus serve as a measure that represents both the impact of government procurement *per se*, as well as the set of other policies that are aimed at stimulating production in the industry. Our analyses therefore focus on estimating the impact of the amount of government procurement.

Minimal fighting took place on Indian soil during World War II, but 2.5 million Indian soldiers fought on the Allied side in a number of war theaters, most importantly against the Japanese in Burma ([Raghavan, 2017](#)). In principle this military service could also have economic effects on soldiers' origin areas. In analyses below we show that including proxies for district-level participation in military service in World War II has no influence on the estimated effect of the shift-share variable. Military service does not appear to be a mechanism through which effects of our shift-share variable operate.

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<sup>4</sup>The total rupee value of war-related public procurement is calculated using [Aggarwal \(1947\)](#). The GDP figure for 1938 is from Appendix Table 6(d), [Sivasubramonian \(2000\)](#).

<sup>5</sup>We do not yet have comprehensive data on these other types of policies, but are actively working to assemble a full picture of such policies.

### 3 Empirical Analyses

We aim to shed light on the impact of war mobilization on Indian economic development in the long run. We present here analyses examining impacts on structural transformation – the shift of employment from agriculture to the modern sectors (industry and services).

The causal variation we exploit is variation across industries in the magnitude of World War II procurement by the British colonial government of India, combined with variation across Indian districts in the presence of those industries in the pre-war period. We combine these sources of variation to implement a shift-share research design, which we describe in Section 3.1 below.

The sample for analysis is a panel of 164 Indian locations (“districts”) observed from before to after World War II. In these analyses we take the magnitude of war-related government procurement as the measure of the extent of “war mobilization” across industries. One should therefore interpret our regression coefficients as representing the combined effect of the magnitude of procurement itself, as well as any concurrent government policies to stimulate supply that are correlated with the magnitude of government procurement.

Our primary analyses take the Indian district as the unit of analysis. In Section 3.4 we will also examine outcomes at the level of the national industry (in aggregate for all of India).

#### 3.1 Empirical Approach

To estimate the causal impact of war mobilization on structural transformation of Indian districts, we take a shift-share approach (following [Borusyak et al. \(2022\)](#)) that exploits the district-level incidence of British colonial government World War II procurement across industries.

The intuition for the shift-share strategy is as follows. British wartime procurement varies across industries, with some industries (e.g., munitions) experiencing very high demand, some (e.g., footwear) seeing intermediate levels of demand, and others low or zero wartime demand (e.g., musical instruments, jewelry, pottery). Indian districts also vary in the pre-war presence of different industries, as measured by the distribution of a district’s employment across industries. Some have relatively high shares of employment in industries that experienced war-related demand, such as

munitions and footwear, while other districts have low such shares. Districts with higher pre-war employment shares in war-related industries should experience higher increases in demand (on a per worker basis) due to war-related government procurement. Our approach involves creating a shift-share variable quantifying the extent to which a district experienced World-War-II-related procurement. This variable will be the causal variable of interest in our analyses.

To account for border changes over time, we combine administrative districts so as to be able to track consistently-defined locations from before to after the war using the [Dincecco et al. \(2022\)](#) district concordance. We aggregate Census data appropriately to map to these combined locations. We continue to refer to these combined locations as “districts”. Some districts cannot be included in our current analyses due to data limitations (e.g., pre-war data are absent for much of present-day Rajasthan and Gujarat). We exclude the Andaman and Nicobar Islands since these were occupied by Japan during the war and thus did not provide any war materiel. We also exclude from our analyses districts in the northeast region (which includes Bengal and Assam) because war procurement and production intentionally avoided that region due to the proximity to Japan’s military advance in Burma ([Raghavan \(2017\)](#), p. 321).

The shift-share variable,  $Shiftshare_d$ , is predicted World-War-II-related government procurement per worker in district  $d$ :

$$Shiftshare_d = \sum_i S_i \times \omega_{id,1931} \quad (1)$$

The “shifts” in the shift-share are  $S_i$ , wartime procurement per worker in industry  $i$ : total World War II procurement in industry  $i$  divided by the total number of pre-war (1931) workers in industry  $i$  in British India (procurement is denominated in real 2011 Indian rupees, INR). This is a measure of the magnitude of war-related procurement across industries. In a subset of 45 out of 195 industries, there is non-zero procurement; it is these “war-related” industries on which we focus.<sup>6</sup>

The “shares” in the shift-share are  $\omega_{id,1931}$ , employment in industry  $i$  in district  $d$ , as a share of all employed people in district  $d$  (measured in the closest pre-war Census

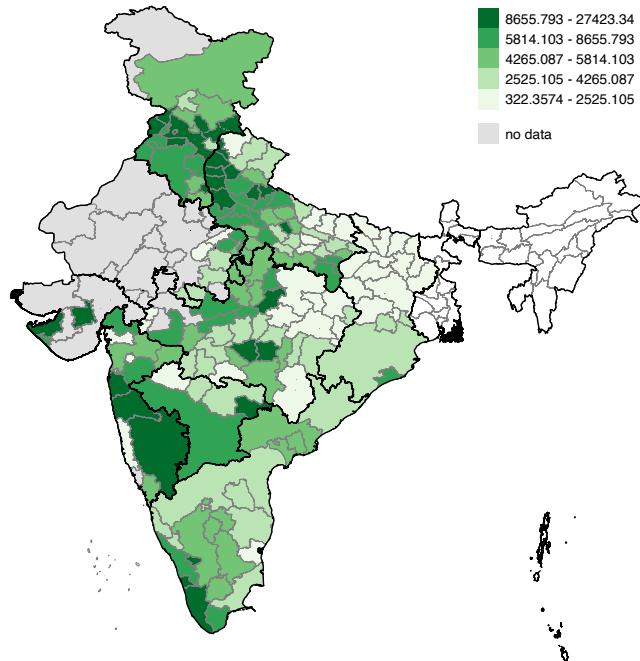
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<sup>6</sup>We exclude some parts of British India from the total count of workers in the denominator of  $S_i$ . We exclude workers in Burma as well as the Andaman and Nicobar Islands, since they were occupied by Japan during the war and thus did not provide any war materiel. We also exclude workers in the northeast region (which includes Bengal and Assam), since war procurement intentionally avoided that region due to fear of Japanese invasion from Burma ([Raghavan, 2017](#)).

year, 1931).  $\omega_{id,1931}$  measures the “exposure” of district  $d$  to war-related procurement in industry  $i$ . We calculate these  $\omega_{id,1931}$  shares for each industry for each district.

Taking the product of the shift  $S_i$  and the share  $\omega_{id,1931}$  for each of a district’s industries, and then summing across the district’s industries, yields the shift-share variable  $Shiftshare_d$ : the predicted total value (in INR) of war-related procurement per worker in district  $d$ . The spatial distribution of the shift-share variable is shown in Figure 1.

Figure 1: Spatial Variation in Shift-Share Variable



Notes: Districts shown are consistent geographic units between 1931 and 2011 Census. Light grey lines demarcate district borders. Black lines demarcate larger-scale “regions” (author defined) of contiguous groups of districts (for estimation of region \* time fixed effects). Green shading represents value of shift-share variable, expression (1), in real 2011 Indian rupees (INR). Grey shading indicates districts for which we cannot calculate the shift-share variable due to availability of Indian Census data. Districts in white (in northeast) are not included in analysis, due to proximity to Japanese military advance in Burma. Andaman and Nicobar Islands also not included in analysis since they were occupied by Japan during the war.

We estimate the following regression equation:

$$y_{dt} = \alpha_d + \beta(Shiftshare_d \times Post_t) + \gamma Post_t + \delta(\mathbf{X}_{d,1931} \times Post_t) + \epsilon_{dt} \quad (2)$$

The sample for each regression we estimate will be a short two-period panel of

districts in one pre-war year (1931) and one post-war year. Post-war periods will be decadal periods corresponding to Indian Census years: 1951 to 2011 inclusive. We will estimate a separate regression in the form of Equation (2) for each post-war period. This allows us to trace the temporal dynamics of effects, by observing how coefficient estimates change across post-war decades.<sup>7</sup>

Variables in Equation (2) are as follows.  $y_{dt}$  is the dependent variable, the share of employment in the modern sector (industry and services, or non-agriculture) of district  $d$  in year  $t$ .

$Shiftshare_d$  is the shift-share variable (expression (1)). This is interacted with  $Post_t$ , an indicator for post-war periods. For ease of interpretation of the regression coefficient, we normalize the shift-share variable to have mean zero and standard deviation one when including it in the regression.

$\alpha_d$  are district fixed effects, which account for any time-invariant differences across districts.  $Post_t$  is the time fixed effect (an indicator for the post-war period), and accounts for any changes over time common to all districts between 1931 and post-war period  $t$ .  $\epsilon_{dt}$  is a mean zero error term.

$\mathbf{X}_{d,1931}$  is a vector of 1931 characteristics of district  $d$ . These are interacted with the  $Post_t$  dummy. First of all, the vector includes the “sum of shares” (sum of  $\omega_{id,1931}$  across war-related industries within districts). This sum of shares varies across districts (and is never equal to 1), making this an “incomplete shares” case in the [Borusyak et al. \(2022\)](#) framework. Conceptually, the sum of shares represents the share of employment in some war-related industry; inclusion of this variable as a control interacted with  $Post_t$  controls for differential trends related with a district’s pre-war employment in war-related industries.

In addition,  $\mathbf{X}_{d,1931}$  includes controls for baseline (pre-war or time-invariant) economic, historical, and geographic characteristics of districts. Interacting  $\mathbf{X}_{d,1931}$  with  $Post_t$  accounts for differential time trends associated with baseline characteristics of districts. Economic controls include share of employment in industry and share of employment in services (share of employment in agriculture is the omitted category). These controls account for any differences in trends across districts related to their pre-war economic characteristics (e.g., if areas that were already more industrialized

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<sup>7</sup>This approach also allows us to maximize the number of districts represented in each regression sample, since combining districts due to border changes only needs to consider border changes between 1931 and the corresponding post-war period. If we were to aim to construct districts that had consistent borders across 1931 and *all* post-war periods, we would end up with substantially fewer (and larger) districts in the analysis, reducing the spatial variation used to estimate our effects.

prior to the war were on different time trends). In addition, economic characteristics include log population, share of population employed, and population density as key pre-war characteristics that may also be associated with differential time trends. Historic controls include share of population under British direct rule, years of prior railroad access, and historical conflict within 250 km (years 1000-1757), from [Dincecco et al. \(2022\)](#).

The vector  $\mathbf{X}_{d,1931}$  also includes region fixed effects (for 11 regions); with this interacted with  $Post_t$ , estimates will be based only on variation in  $Shiftshare_d$  within (and not across) regions. Geographic controls include temperature, precipitation, slope, elevation, land area, and caloric yield in agriculture. Finally, to assess whether correlations between military service and war materiel procurement confounds effect estimates, the vector includes World War II casualties per million, martial castes per thousand, and an indicator for non-missing military controls (from [Jha and Wilkinson \(2012\)](#)).

$\beta$  is the coefficient of interest, and is interpreted as the causal impact of a one-standard-deviation increase in the shift-share variable on the share of employment in the modern sectors of the economy. It is identified from changes in the dependent variable for a district over time that are associated with the district's value of the shift-share variable, net of time trends associated with the vector of controls  $\mathbf{X}_{d,1931}$ .

In the [Borusyak et al. \(2022\)](#) shift-share approach, causal identification depends on the exogeneity of the shifts (shocks), rather than the shares. Our identification assumption is that World War II purchases from industry  $i$  are as good as randomly assigned (conditional on district- $d$ -level pre-war controls). Shares  $\omega_{id,1931}$  can actually be endogenous.

We provide a partial test of the identification assumption by showing a pre-trend (“placebo” or “false” experiment) regression analysis alongside the main regression results. This is analogous to tests of “parallel trends” in difference-in-difference research designs. The pre-trend test will show that the pace of structural transformation (the change in the share of employment in the modern sectors) was not faster in the pre-war decades (between 1921 and 1931) in districts that *would in the future receive* higher World-War-II-related government purchases (districts that would have higher  $Shiftshare_d$ .) This test rules out that government World War II purchases were targeted (intentionally or inadvertently) towards districts that were already on steeper economic growth trajectories prior to the war.

Table 1: Major Categories of Products Procured

Product Category	Total Value of Orders (2011 INR)	% of Total
Food Items	156,294,371,446	21.02
Woollen Textiles (Other than factory production)	95,787,392,268	12.88
Cotton Textiles (Other than factory production)	93,055,582,789	12.51
Factory Items - Clothing	77,001,141,426	10.36
Engineering Stores	62,503,547,062	8.41
Vehicles	56,885,281,672	7.65
Miscellaneous	48,042,672,398	6.46
Factory Items - Munitions	43,317,151,048	5.83
Leather	42,808,598,866	5.76
Timber	37,440,779,350	5.04
Factory Items - Harness and Saddlery Items	24,270,857,059	3.26
Shipbuilding	6,186,038,960	.83
Total	743,593,410,560	

*Notes:* Table lists value of products by category procured by Department of Supply in British India for the World War II effort, from Aggarwal (1947). Total value of procured products by category are summed across 1939-1946, expressed in real (2011) Indian rupees (INR) (Sivasubramonian 2000).

### 3.2 Data

Our most unique data source is the reference we use to construct our shift-share “shifts”,  $S_i$  (government wartime procurement in each industry  $i$ ). The data come from the book *History of the Supply Department* (Aggarwal, 1947). This source reports the value of World-War-II-related procurement by the British colonial government of India, in Indian rupees (INR), for 384 detailed products from 1939 to 1946. These so-called “supply orders” were placed by the Supply Department of the colonial government of India, which was responsible for sourcing goods for the World War II effort from India. The supply order data are reported at the national (India) level, by product.

We display the top 20 of the 384 products by value of goods procured in Appendix Table A1. The largest product, cotton tent components, saw World War II procurement amounting to INR 63 billion. The other products in the top 20 illustrate the variety of products procured, across food products, clothing, footware, and heavy equipment. Table 1 aggregates products into major categories. Food items is the top category, amounting for 21.0% of total procurement by value. Three categories related to textiles and clothing each amount to 10-13% of the total. Heavier industrial categories are also present, such as engineering stores (8.4%), vehicles (7.7%), munitions (5.8%), and shipbuilding (0.8%).

Data on the shift-share “shares”  $\omega_{id,1931}$  of employment by industry are from the

Table 2: Top 10 Industries by Orders per Worker

Census Occ Code	Census Occupations 1931	Orders per worker (INR)
91	Making, assembling or repairing motor vehicles or cycles	5,976,304
93	Ship, boat, aeroplane builders	3,223,575
58	Makers of arms, guns, etc	2,161,173
66	Matches, fireworks and other explosives	2,134,918
177	Architects, surveyors, engineers and their employees	1,830,416
81	Others (Food industry)	1,611,488
70	Others (Chemical products)	1,044,478
94	Heat, light, electricity, motive power, etc	996,502
44	Jute pressing, spinning and weaving	807,801
46	Wool carding, spinning and weaving	654,857

*Notes:* Table displays value of shiftshare “shift” ( $S_i$  in expression (1)) for the 10 industries with the highest values (orders per worker). Orders per worker is total value of procured products in the industry divided by India-wide workers in the industry. Calculated using product-level procurement data from Aggarwal (1947), concorded to occupations in the 1931 Indian Census. Orders are summed across 1939-1946, in real (2011) Indian rupees (INR). Worker counts by industry are from 1931 Indian Census.

1931 Indian Census (the last Indian Census before World War II). We use data from this pre-war Census to ensure the shares are predetermined with respect to World War II. We create a concordance between the 384 products in Aggarwal (1947) and the 195 occupations in the 1931 Indian Census.

We display the value of the shift  $S_i$  (total purchases over 1939-1946 per worker in the industry, in real 2011 INR) for the top 10 industries in Table 2. The value of  $S_i$  is largest in the following three industries: making, assembling or repairing motor vehicles or cycles (INR 5,976,304); ship, boat, aeroplane builders (INR 3,223,575); makers of arms, guns, etc. (INR 2,161,173); and manufacture of matches, fireworks, and other explosives (INR 2,134,918). On the other end of the scale,  $S_i$  takes very small values for potters and makers of earthenware (INR 940) and cabinet makers, carriage painters, etc. (INR 543), and is zero for other industries (e.g., jewelry, musical instruments).

To get a sense of the variation in the shares  $\omega_{id,1931}$  (share of pre-war employment in industry  $i$  in district  $d$ ), consider the cotton spinning, sizing, and weaving industry. The standard deviation of  $\omega_{id,1931}$  for this industry across districts is 0.015. The maximum of  $\omega_{id,1931}$  for this industry is 0.089, for a district consisting of Bijnor (Uttar Pradesh) and its surrounding rural area. Surguja district (Chhattisgarh) is at the median, with  $\omega_{id,1931}$  of 0.0126. At the other extreme, the district of Dang (Gujarat) has an  $\omega_{id,1931}$  of zero for this industry.

Since district borders change over time, we use the [Dincecco et al. \(2022\)](#) concordance to define districts that are consistent geographical units between 1931 and any post year that we consider in our regression analysis. We refer to these consistent geographical units as “districts”. These are shown with grey borders in Figure 1 for the 1931-2011 sample. We also combine multiple districts to form geographically contiguous areas which we call “regions” (the areas surrounded by black borders in Figure 1). These 11 regions are the basis of the region \*  $Post_t$  fixed effects included in the regression.

For data on our outcome variable (share of employment in modern sectors), as well as 1931 economic controls, we conducted data entry of tabulated district-level variables from the 1921, 1931, 1951, 1961, 1971, and 1981 Indian Censuses. (There was no census in 1941.) Creation of the exposure shares  $\omega_{id,1931}$  also required us to conduct data entry for employment by industry from the 1931 census. Census data for 1991, 2001 and 2011 were already available in electronic form.

The summary statistics for key variables are shown in Table 3. The share of employment in the modern sectors (non-agriculture) rises between 1931 and 2011 by 9.3 percentage points, indicating some structural transformation over the course of 80 years. There is considerable variation in the shift-share variable  $Shiftshare_d$ : it has mean INR 5,558.03 and standard deviation INR 4510.53 (2011 INR). A point of reference for these magnitudes is wartime Indian GDP per capita, 12,133 (in 2011 INR); so the standard deviation of  $Shiftshare_d$  is about 37% of per capita GDP at the time.<sup>8</sup>

All data in Indian rupees (INR) in this paper are expressed in real 2011 units. Conversion to real 2011 units uses GDP deflators from [Sivasubramonian \(2000\)](#) and the World Bank’s World Development Indicators.

### 3.3 Results

We now present regression estimates of the impact of wartime mobilization on long-run structural transformation.

In Table 4, we present estimates for the 1931-2011 sample in the first five columns. The dependent variable is share of employment in the industry and services sectors (the modern sectors). We present  $\beta$  estimates from equation (2) with different sets of

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<sup>8</sup>This GDP per capita figure is the 1936-45 average, expressed in 2011 INR ([Sivasubramonian, 2000](#)).

Table 3: Summary statistics for 1931-2011 sample

Variables	Mean	SD
<b>Dependent Variables</b>		
Share employed in modern sector (1931)	.282	.152
Share employed in modern sector (2011)	.372	.173
<b>Shift-share Variables</b>		
<i>Shiftshare<sub>d</sub></i>	5588.031	4510.53
Sum of shares ( $\sum_i \omega_{id, 1931}$ )	.077	.042
Shiftshare (Industry)	5377.123	4152.108
Sum of shares (Industry)	.071	.036
Shiftshare (Light Industry)	4034.266	2657.503
Sum of shares (Light Industry)	.061	.033
Shiftshare (Heavy Industry)	1342.857	2507.844
Sum of shares (Heavy Industry)	.011	.008
<b>Controls (1931)</b>		
Population (000)	1395.251	1569.414
Share of employed in industry	.147	.075
Share of employed in services	.135	.101
Share of population employed	.483	.088
Population density	5.529	65.273
Direct British Rule	.739	.431
Historical conflicts within 250km (1000–1757)	.129	.138
Years of prior railroad access (to 1934)	50.604	20.876
Temperature	24.877	3.528
Precipitation	1182.599	534.315
Slope	.508	.885
Elevation	410.163	598.445
Total land area (sq km)	31.361	125.851
Avg max caloric yield (000s)	6653.65	1140.778
WWII casualties per million	471.331	1315.804
Martial castes per thousand	41.559	141.888
War controls non-missing	.811	.371

*Notes:* Number of districts in 1931-2011 sample is 164. “Modern sector” is industry and services (i.e., non-agriculture). “Sum of shares” is equivalent to 1931 share of employment in war-related industries. Sum of shares and control variables are interacted with post-war indicator ( $Post_t$ ) when included in regression to account for time trends associated with pre-war characteristics.

Table 4: Regression Results: Impact of World-War-II-Related Government Purchases on Structural Transformation in Indian Districts, 1931-2011

	1931-2011 Sample					1921-1931 Sample (Pre-Trend Test)
	(1)	(2)	(3)	(4)	(5)	(6)
Shiftshare $\times Post_t$	0.08062*** (0.02061)	0.06203*** (0.01937)	0.06378*** (0.02113)	0.05564** (0.01868)	0.05698*** (0.01949)	-0.01887 (0.01602)
District F.E.	YES	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES	YES
1931 Economic Controls $\times Post_t$	YES	YES	YES	YES	YES	YES
Historic Controls $\times Post_t$	NO	YES	YES	YES	YES	YES
Region FE $\times Post_t$	NO	NO	YES	YES	YES	YES
Geographic Controls $\times Post_t$	NO	NO	NO	YES	YES	YES
Military Controls $\times Post_t$	NO	NO	NO	NO	YES	YES
Num. Obs	328	328	328	328	328	284

*Notes:* **Dependent variable** is employment in modern sectors (industry and services) as share of total employment. 164 districts observed in 1931 and 2011. All regressions include district and year fixed effects. Controls interacted with  $Post_t$  are all from pre-WWII period or time-invariant. **Economic controls** (from 1931 Census) are log population, share population employed, production workers as share of employment, service workers as share of employment, population density, and shift-share “sum of shares” (share of workers in any war-related industry).

**Historic controls** (from Dincecco et al. (2022)) are share of population under British direct rule, years of prior railroad access, and historical conflict within 250 km (years 1000-1757). **Region fixed effects** are for 11 regions. **Geographic controls** are mean temperature, mean precipitation, mean slope, mean elevation, land area, and maximum caloric yield in agriculture. **Military controls** (from Jha and Wilkinson (2012)) are WWII casualties per million, martial castes per thousand, and indicator for non-missing military controls. Standard errors are exposure-robust, accounting for correlation of shocks across districts, based on estimation of shock-level (industry-level) regressions (Borusyak et al., 2022).

controls.  $\beta$  estimates are interpreted as the impact of one-standard-deviation higher shift-share variable on the fraction of workforce in the modern sectors.

Column 1 includes district fixed effects, period fixed effects, and 1931 economic controls interacted with  $Post_t$ . In column 2, we add interactions of historical controls with  $Post_t$ . In column 3, we include region fixed effects interacted with  $Post_t$ , which allows regions to be on different time trends (capturing spatially-correlated time-variant factors such as weather shocks, or region-specific economic trends or government policies); with these included in the regression, the coefficient estimate exploits only variation in the shift-share variable across districts within the same region. In column 4, we add geographic controls interacted with  $Post_t$ . In column 5, we add controls proxying for military service in World War II interacted with  $Post_t$ .

The coefficient on the shift-share variable declines in magnitude slightly between columns 1 and 2 (from 0.081 to 0.062), but remains relatively stable thereafter as additional controls interacted with  $Post_t$  are added to the regression. The stability of

the coefficient between columns 2 and 3, when region fixed effects (times  $Post_t$ ) are added to the regression, suggests that cross-district spillovers are not substantial. The fact that the coefficient is stable between columns 4 and 5, when military service controls (times  $Post_t$ ) are added to the regression, indicates that the coefficient on the shift-share variable is not also capturing (or confounded with) impacts of military service in the war.

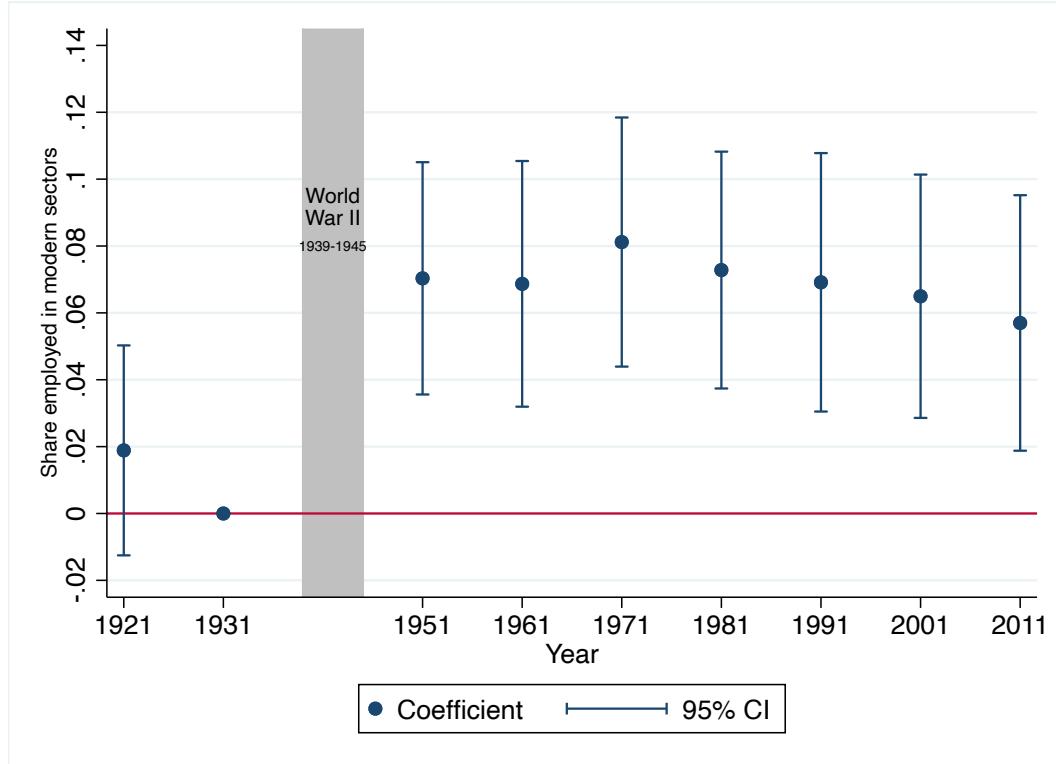
In column 5, with all sets of controls interacted with  $Post_t$  included, the coefficient indicates that a one-standard-deviation increase in the shift-share variable raises modern sector employment by 5.7 percentage points. The magnitude of this effect is not small, amounting to about one-third of a standard deviation of the outcome variable.

In column 6, we present results of the pre-trend test (“placebo” or “false” experiment) regression. The regression specification is the same as in column 5, but each district’s data are from the two pre-war decades (1921 and 1931), and we let  $Post = 1$  in 1931. (Due to missing 1921 data, the sample size of this regression is smaller than in the first three columns. Results in the first five columns are robust to restricting the sample to the same districts included in the regression of column 6.) The coefficient estimate in this pre-trend regression is negative, small in magnitude, and not statistically significantly different from zero. This pre-trend test provides no indication that districts that would in the future receive higher World War II product demand were on a faster growth trajectory in the pre-war period.

### 3.3.1 Dynamics of Effect Over Time

We have also conducted similar analyses of treatment effects over other decadal time spans, corresponding with Indian Census rounds. Census outcome data (share of employment in industry and services) were already available electronically for 1991 and 2001, and we also conducted data entry for Census outcome data for 1951-1981. We run regressions analogous to those of column 5 of Table 4. For the post-war years, regressions take 1931 as the pre-war year and a decadal observation from 1951 to 2011 inclusive as the post-war year (the latter estimate will be identical to the estimate in column 5 of Table 4). We also show the pre-trend test using data from 1921 and 1931 (where the reference year is taken to be 1931 for the purpose of this figure; the coefficient is therefore identical to the coefficient in column 6 of Table 4, but opposite in sign).

Figure 2: Event Study: Impacts of War Procurement on Employment in the Modern Sectors (Industry and Services)



Notes: Coefficient estimates using specification of column 5, Table 4, for different time periods (with 95% confidence intervals). Point estimates displayed are effects of one-standard-deviation increase in shift-share variable. Dependent variable is district's share of employment in modern sectors (industry and services). For list of control variables and other details, see Table 4. In regressions for post-war periods, pre-war (reference) year is 1931, and post-war year is either 1951, 1961, 1971, 1981, 1991, 2001, or 2011. Figure also shows "pre-trend" test using data from 1921 and 1931, with 1931 as reference year for purpose of this figure (coefficient is identical to but opposite in sign of coefficient in column 6 of Table 4).

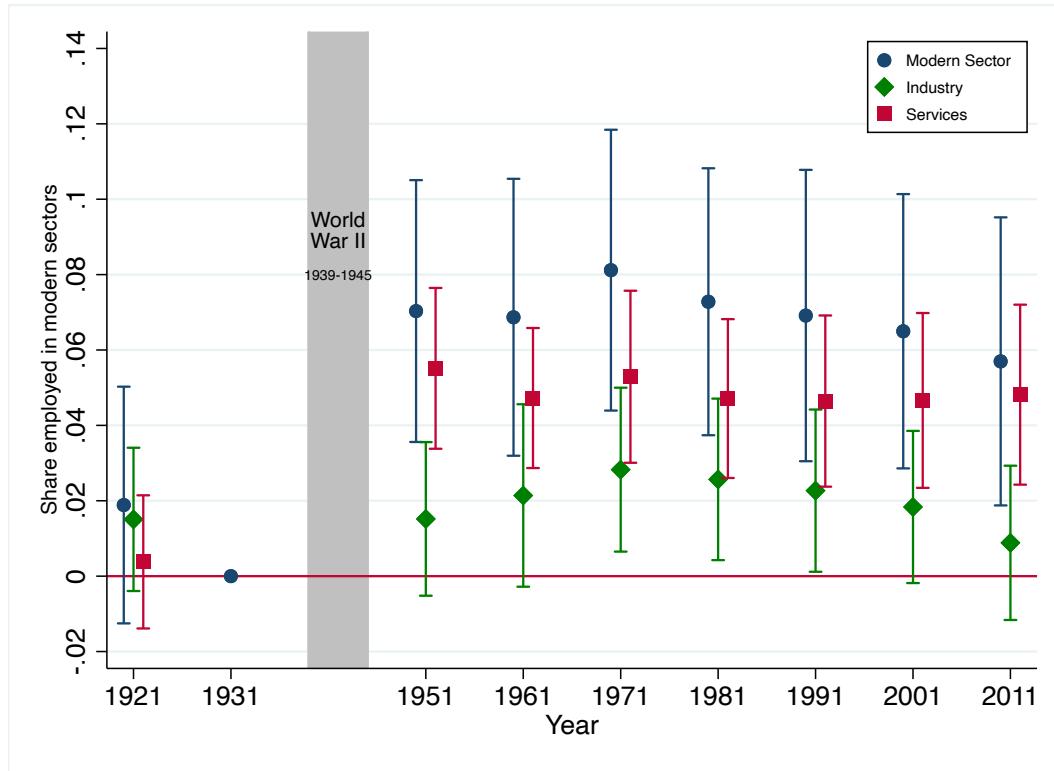
We present all these coefficient estimates in an event study diagram, Figure 2. The World War II years are depicted as a vertical gray rectangle. In all post-war time periods, the coefficient estimate is positive and statistically significantly different from zero (at the 1% level in all cases). Districts that received one standard deviation higher orders per worker have 7 percentage points higher share of employment in the modern sectors in 1951. The effect size is quite stable over the decades: the peak is 8.1 percentage points in 1971, and the smallest coefficient is the 2011 value of 5.7 percentage points. The figure also makes clear the absence of a pre-trend in the pre-war period (1921-1931).

### 3.3.2 Effects on Industry and Services Employment

The estimates we have presented so far are effects on total modern sector employment (industry and services). It is also of interest to examine effects on industry and service sector employment separately. This analysis can shed light on cross-sector spillovers, since the vast majority of war procurement was in industrial (not services) sectors.

We run regressions analogous to those in Figure 2, but separately for share of employment in services and share of employment in industry. Figure 3 is the event study figure capturing these regression results. The coefficient (and 95% confidence interval) for employment in industry is displayed in green, and corresponding estimates for services are displayed in red. For comparison, the estimates for the total modern sector (industry plus services) are shown in blue (which replicates the results in Figure 2).

Figure 3: Event Study: Impacts on Industry and Services Employment Separately



Notes: This figure replicates estimates of Figure 2 (in blue), and adds coefficient estimates for regressions run separately for share of employment in industry (in green) and share of employment in services (in red). All other details are as in notes of Figure 2.

The majority of effects on modern sector employment are driven by the services

sector. In each time period, the coefficient estimate for services employment is larger than the corresponding coefficient for industry employment. While this result is strongly suggestive of cross-sector spillovers – because the vast majority of war procurement orders are in the industrial sectors – it is possible to make this point more clearly by estimating the impact of war procurement in *only* the industrial sectors, excluding non-industrial sectors.

We therefore run analogous analyses but with an alternate shift-share variable that excludes war procurement in non-industrial sectors: services and agriculture, which account for 1.5% and 2.5% of war procurement, respectively. Any estimated impacts of this industry-only shift-share measure on services employment would be clearly interpretable as a cross-sector spillover from industry to services employment.

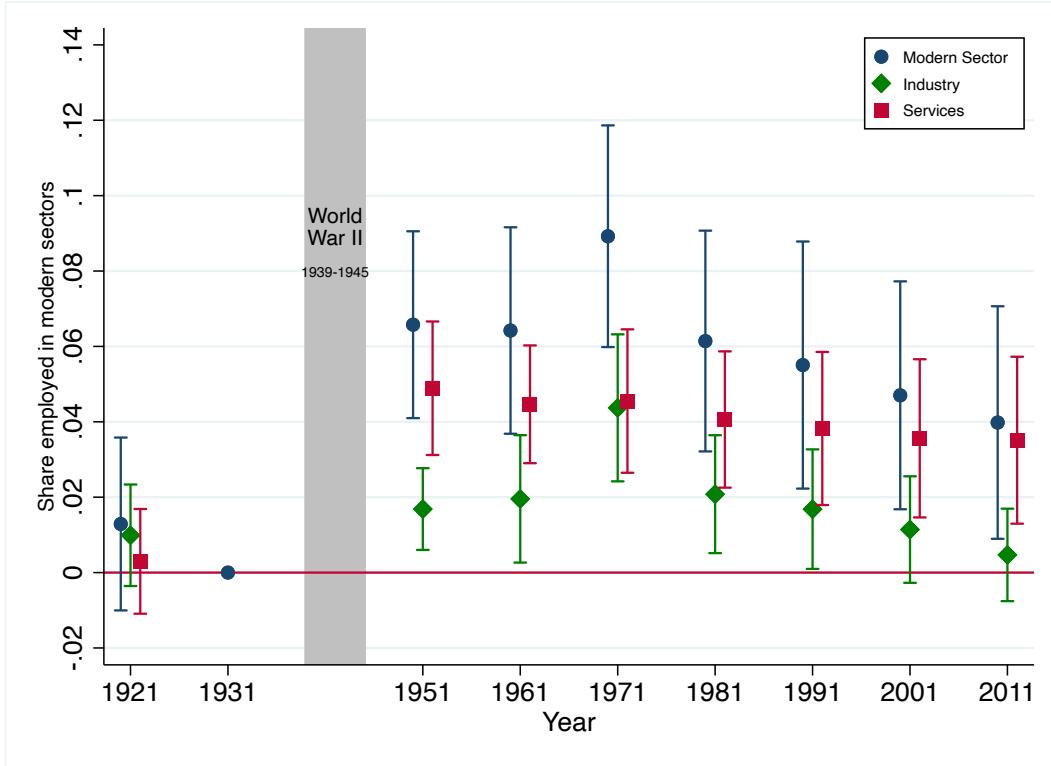
We display the event-study coefficients from this analysis in Figure 4. The coefficient estimates for industry, services, and total modern sector employment are similar in magnitude and statistical significance levels to those in Figure 3. There is a positive effect on both services and industry employment in all periods, with the effect on services employment always larger than that on industry employment. These results reveal quite substantial spillovers of wartime industrial procurement to the service sector.

### 3.3.3 Impacts on Services Subcategories

The cross-sector spillovers from industrial war procurement to service sector employment are consistent with models that emphasize the importance of coordination externalities, such as [Murphy et al. \(1989\)](#). The key mechanism in the model of the “big push” in [Murphy et al. \(1989\)](#) is worker purchasing power: when firms coordinate to invest at the same time, aggregate worker purchasing power rises, fueling demand for goods and services broadly in the economy. The economy is thus able to sustain the high-investment equilibrium, associated with higher employment in the modern sectors. This mechanism has been highlighted recently by [Goldberg and Reed \(2023\)](#), who emphasize the importance of domestic market size in driving aggregate household demand in all sectors of the economy, including nontradables such as services.

To shed light on whether household demand for services may be driving the cross-sector spillovers we have documented so far, we examine impacts of the industry-only shift-share variable on categories of services occupations. We examine as an outcome variable the share of employment in “consumer” services that are primarily demanded

Figure 4: Impacts of Industry-Only Shift-share



Notes: This figure replicates estimates of Figure 3, but replacing the shift-share variable with an analogous shift-share variable that excludes procurement in services and agriculture (respectively accounting for 1.5% and 2.5% of procurement by value). All other details are as in notes of Figure 2.

by households (e.g., retail trade, restaurants, personal services). We also examine “business” services that are mainly purchased by firms (e.g., transport, logistics, accounting, office clerks), as well as the services subsectors of health, education, and government.

Regression results for the 1931-2011 period are in Table 5. All regressions include the full set of control variables (as in column 5 of Table 4 and Figures 2 through 4). The coefficient estimates are all interpreted as the impact of a one-standard-deviation increase in the shift-share variable on the fraction of the workforce in the given services subcategory. The largest coefficient is in the regression for consumer services, 2.0 percentage points, and statistically significant at the 1% level. The coefficient for business services is also substantial (1.1 percentage points, significant at the 5% level), but smaller than for consumer services. Coefficients for health and education services are small in magnitude and not statistically significantly different

from zero. We also find a positive effect on government services that is small in magnitude (0.3 percentage points) and significant at the 1% level.

Table 5: Regression Results: Impact of World-War-II-Related Government Purchases on Share of Workforce in Service Sub-Categories, 1931-2011

	(1) Consumer	(2) Business	(3) Health	(4) Education	(5) Government
Shiftshare $\times Post_t$	0.02011*** (0.00548)	0.01105** (0.00555)	0.00039 (0.00029)	0.00021 (0.00065)	0.00343*** (0.00122)
Dependent Variable Mean - 1931	.06	.049	.002	.003	.017
Dependent Variable Mean - 2011	.089	.049	.009	.024	.023
Num. Obs.	328	328	328	328	328

*Notes:* Dependent variable is employment (as share of total employment) in services subcategories: consumer, business, health, education, and government. 164 districts observed in 1931 and 2011. Independent variable is industry-only shift-share. In the computation of this shift-share, procurement in services and agriculture are excluded. All regressions include district and year fixed effects. Each column includes economic, historic, geographic and military controls interacted with  $Post_t$  (see Table 4 for the full list). Standard errors are exposure-robust, accounting for correlation of shocks across districts, based on estimation of shock-level (industry-level) regressions (Borusyak et al., 2022).

The fact that consumer services shows the largest response to the shift-share variable is consistent with theoretical models such as Murphy et al. (1989) that emphasize coordination externalities operating via aggregate worker demand. It also appears that spillovers via firms' demand for business services are not insignificant. There is a positive response of government employment, perhaps reflecting provision of public services in response to growth of the modern economic sectors.

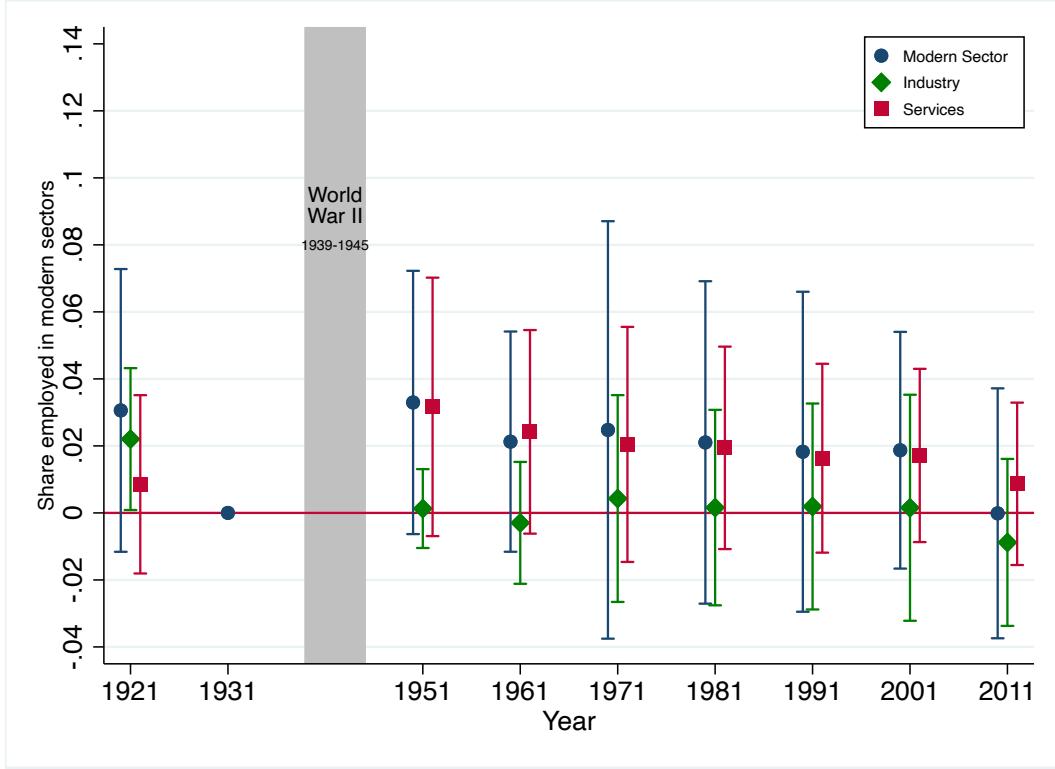
### 3.3.4 Light- vs. Heavy-Industry Shiftshare

It is also of interest to examine impacts of procurement of different types of industrial products, in particular light versus heavy industrial goods. We can construct a shift-share variable representing only procurement of light industrial goods (e.g., clothing, textile products, footwear, food products) and separately a shift-share variable for heavy industrial goods (e.g., vehicles, munitions, engineering stores, and chemical products). The relative magnitude of effects of light vs. heavy industry procurement could reveal the importance of information or learning externalities.

We run regressions for our main outcome variables (employment in modern sector, industry, and services) with shift-share variables defined for light industry only and heavy industry only. We present event-study figures summarizing these results in for the light-industry shift-share variable (Figure 5) and the heavy-industry shift-share

variable (Figure 6). As in prior analyses, point estimates presented represent effects of a one-standard-deviation increase in the relevant shift-share variable.

Figure 5: Light Industry Shiftshare

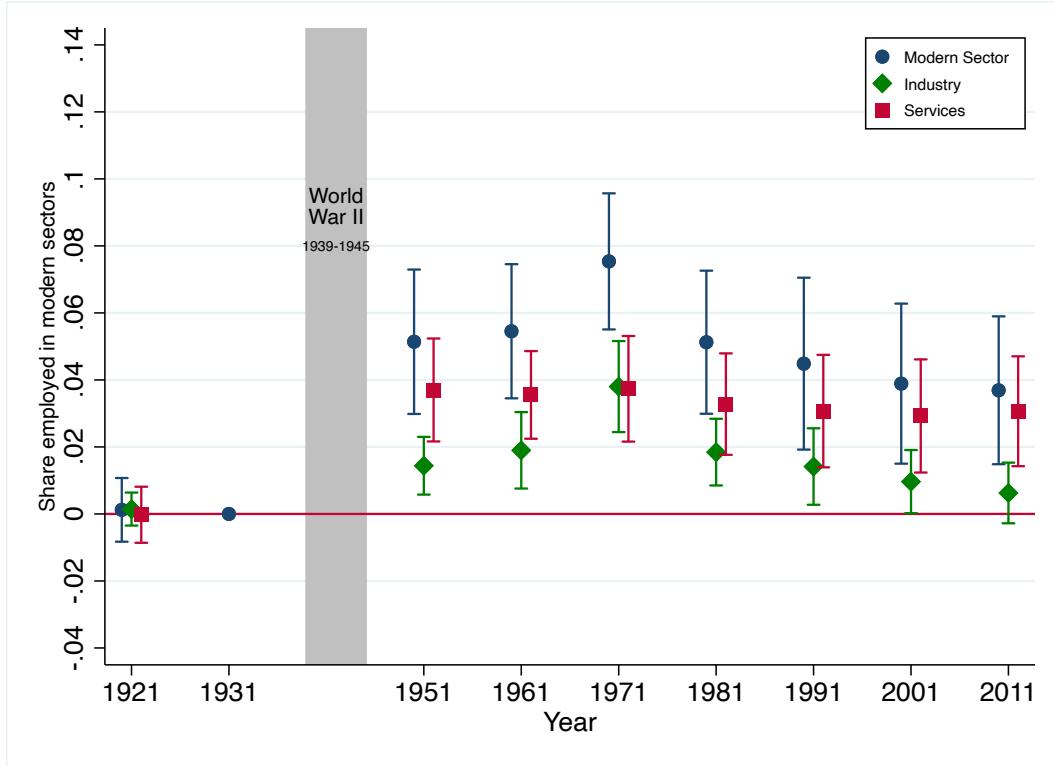


Notes: This figure replicates estimates of Figure 3, but replacing the shift-share variable with an analogous shift-share variable that includes procurement in light industries only. All other details are as in notes of Figure 2.

It is apparent from comparing Figures 5 and 6 that the largest share of effects we have seen in the prior analyses are driven by heavy industry procurement. Coefficients in Figure 5 reveal that light-industry procurement has no effect on industrial sector employment, and a modest effect on service sector employment (around 2 percentage points on average across decades, never statistically significant in any decade). By contrast, patterns of effects in Figure 6 reveal positive effects of heavy industry procurement on both services and industry employment. Effects on services are always statistically significant at conventional levels, and are nearly always larger in magnitude than the effects on industry employment. Effects on industry employment are themselves statistically significant at conventional levels in all years except the final one, 2011.

The fact that structural transformation is primarily driven by heavy industry

Figure 6: Heavy Industry Shiftshare



Notes: This figure replicates estimates of Figure 3, but replacing the shift-share variable with an analogous shift-share variable that includes procurement in heavy industries only. All other details are as in notes of Figure 2.

procurement may reflect the importance of information externalities as a mechanism, for example learning-by doing ([Arrow, 1962](#)) and knowledge spillovers across firms ([Hausmann and Rodrik, 2003](#)). Production techniques for heavy industrial goods would have been closer to the world technological frontier than for light industrial goods. The potential for learning-by-doing and knowledge spillovers across firms would therefore have been greater for heavy industrial goods. The fact that effects we find on modern-sector employment are driven by heavy industry procurement points strongly towards these kinds of informational externalities.

### 3.4 Industry-Level Analyses

Our analyses so far have emphasized cross-sector spillovers from industry to services. It is also of interest to examine cross-sector spillovers solely between industrial sectors. In particular, we seek evidence of upstream and downstream linkages – indirect

effects extending from industries experiencing World-War-II-related demand to other industries that either supply the directly affected industry (upstream linkages) or that demand intermediate goods from the directly affected industry (downstream linkages). Such linkages were first emphasized by [Hirschman \(1961\)](#) as a rationale for industrial policy, and empirical evidence for such linkages has been found by [Choi and Levchenko \(2021\)](#) and [Lane \(forthcoming\)](#).

To test for upstream and downstream linkages, we conduct analyses at the level of the national industry in India, because upstream and downstream linkages can operate nationally (via trade in inputs), not just within districts. To construct upstream and downstream links between industries, we use the input-output table from [Saluja \(1972\)](#). This table provides information on input-output linkages for 144 industries for the year 1964-1965. We restrict our analysis to the 72 Census occupations that we are able to concord with the industries covered in [Saluja \(1972\)](#). Our outcome variable is log employment in the occupation, as recorded in the Census.

Let  $i$  and  $j$  denote the producing and consuming sectors respectively.  $\alpha_{ij}$  is the input from sector  $i$  to sector  $j$  and denotes the raw materials consumed by  $j$  from  $i$  in the production process. We first construct  $\gamma_{ij}$  to measure the relative importance of input  $i$  in production of  $j$ .

$$\gamma_{ij} = \frac{\alpha_{ij}}{\sum_i \alpha_{ij}} \quad (3)$$

Using total war orders received by industry  $j$  ( $V_j$ ), we construct the upstream and downstream linkages per worker in industry  $i$  as

$$Upstream_i = \frac{\sum_j \gamma_{ij} \times V_j}{\text{Total workers in industry } i \text{ in 1931}} \quad (4)$$

$$Downstream_i = \frac{\sum_j \gamma_{ji} \times V_j}{\text{Total workers in industry } i \text{ in 1931}} \quad (5)$$

$Upstream_i$  represents “upstream” linkages, which are effects on (upstream) industry  $i$  resulting from war procurement in (downstream) industries  $j$  that demand inputs from industry  $i$ .  $Downstream_i$  represents “downstream” linkages: effects on (downstream) industry  $i$  resulting from war procurement in (upstream) industries  $j$  that supply inputs to industry  $i$ .

We estimate the following regression on a national-level panel of industries (two

observations per industry, for 1931 and 2011):

$$y_{it} = \theta_i + \gamma_t + \mu(S_i \times Post_t) + \beta(Upstream_i \times Post_t) + \delta(Downstream_i \times Post_t) + \tau(y_{i,pre} \times Post_t) + \epsilon_{it} \quad (6)$$

$y_{it}$  is log workers in industry  $i$  in year  $t$ .  $\theta_i$  are industry fixed effects and  $\gamma_t$  are period fixed effects.  $S_i$  is orders per worker in industry  $i$  (the “shift” in the shift-share variable, expression (1) above).

$Upstream_i$  and  $Downstream_i$  are as defined in equations (4) and (5).  $S_i$ ,  $Upstream_i$  and  $Downstream_i$  are interacted with the indicator for the post-war period  $Post_t$ .  $y_{i,pre}$  refer to pre-WWII (1931) log workers in industry  $i$ , making this an ANCOVA specification.  $\epsilon_{it}$  is the mean zero error term.

Table 6: Shift, upstream and downstream linkages (1931-2011)

VARIABLES	(1) Log Workers	(2) Log Workers
Shift × Post	0.327 (0.202)	
Upstream × Post	0.065 (0.302)	
Downstream × Post	0.248 (0.332)	
Log Shift × Post		0.058* (0.030)
Log Upstream × Post		0.004 (0.063)
Log Downstream × Post		0.107 (0.105)
industry FE	YES	YES
Year FE	YES	YES
No. of industries=	72	72
Obs=	144	144

*Notes:* Coefficient estimates from equation (6). Dependent variable is log workers in industry  $i$ .  $S_i$  are wartime procurement per worker in industry  $i$ . Upstream and downstream linkages per worker are as defined in expressions (4) and (5).

Regression results from estimating equation (6) are shown in Table 6. In column 1, we show results for a regression where we normalize  $S_i$ ,  $Upstream_i$ , and  $Downstream_i$  to have mean zero and unit standard deviation, so that each coefficient is interpreted as the impact of a one-standard-deviation increase. In column 2 we show regression results where the right-hand-side variables of interest are logged (non-normalized)  $S_i$ ,  $Upstream_i$ , and  $Downstream_i$ , making this a log-log specification.

In column 1, coefficients on  $S_i$ ,  $Upstream_i$ , and  $Downstream_i$  are each positive, but none are statistically significantly different from zero. In column 2, the log-log specification, we find that 10% higher orders per worker in industry  $i$  leads to 5.8% more workers in that industry in 2011 (statistically significant at the 10% level). Coefficients on  $Upstream_i$  and  $Downstream_i$  are positive but not statistically significantly different from zero.

All told, we find no strong evidence here of upstream and downstream linkages between industrial sectors. That said, the coefficients are somewhat imprecise: 95% confidence intervals admit relatively large effects, particularly of downstream linkages.

## 4 Conclusion

Mobilization for war is one of the most prominent and costly activities undertaken by governments. Public decisions to mobilize for war must take into account a wide range of considerations – in, for example, the ethical, political, and social realms. This research deepens our understanding of the *economic* consequences of mobilizing for war. We shed light on these issues in an important context: the world’s most populous country, India. That India is a developing country is also important, as there is very little empirical research on the consequences of war mobilization in developing countries. Our analysis also reveals very long-run impacts, over several decades. Our findings revealing the long-run economic impacts of war mobilization in a developing country can help guide debates and decision-making about participation in war in developing countries around the world.

Economic policies to mobilize for war have substantial overlap with “industrial policies” undertaken by governments, in that they both seek to shape the industrial composition and output of an economy. Our study therefore also contributes to our understanding of the long-run impacts of a type of industrial policy on economic development: in particular, policies that seek to promote the development of industrial sectors. Policy-makers should take account of our findings that temporary policies that seek to promote industrial sectors in the short run can have quite lasting impacts in the long run, persistently altering the industrial structure of the economy.

There are several important avenues for future research. It is of interest to examine a set of other district-level outcomes that it is possible to track in the Indian Census and other datasets from before to after World War II. Outcomes available in

the Census include literacy (a basic human capital measure) and female labor force participation. Firm-level and international trade datasets (many of which require additional investments in data entry) will allow us to estimate impacts on firm outcomes and exports. In addition, we believe another important question is whether post-independence economic policies may have responded to World War II economic mobilization, either magnifying or attenuating the impacts of the World War II procurement in subsequent decades. Of particular interest in this vein are the heavy industrial development policies implemented starting in the 1950s, until the economic liberalization starting in the mid-1980s. It would be important to examine whether these post-independence industrialization policies tended to be targeted to the same industries and districts that received World War II procurement orders, serving as a potential mechanism through which the impacts of World War II procurement propagated over subsequent decades.

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## Appendix A

Table A1: Top 20 Procured Products in Aggarwal (1947)

Product	Product Category	Value of Orders (INR, thousands)
Cotton Tent Components (Flies, Walls, etc.)	Cotton Textiles	63,382,578
Ghee	Food Items	40,767,138
Timber - General Purpose	Timber	32,590,300
Vehicles and Chassis	Vehicles	30,918,373
Sand Bags	Woollen Textiles	26,502,801
Atta	Food Items	19,551,383
Batteries & Cells, various sizes and types	Engineering Stores	17,830,618
Rice	Food Items	16,179,445
Boots Ankle	Leather	16,083,376
Vehicles and lorry bodies	Vehicles	15,914,896
Hessian Cloth	Woollen Textiles	12,361,841
Cement	Engineering Stores	12,305,738
Socks Woollen	Woollen Textiles	12,286,220
Sugar	Food Items	10,752,845
E.D. Parachute Cotton Com-18, diameter	Clothing	9,874,211
Blankets Bawaok	Woollen Textiles	9,440,144
Serim Hessian Strips	Woollen Textiles	8,654,438
Bitumen	Engineering Stores	8,630,717
Web Equipment	Harness and Saddlery Items	8,155,310
Snap Fasteners	Miscellaneous	7,293,739

*Notes:* Table lists top 20 products by value procured by Department of Supply in British India for the World War II effort, from Aggarwal (1947). Value of products procured are summed across 1939-1946, expressed in thousands of real (2011) Indian rupees (INR) (Sivasubramonian 2000).