Online Appendix for "Can stimulating demand drive costs down? World War II as a natural experiment"*

François Lafond[1,2], Diana Greenwald[3], and J. Doyne Farmer[1,2,4]

[1]*Institute for New Economic Thinking at the Oxford Martin School*
[2]*Mathematical Institute, University of Oxford*
[3]*Isabella Stewart Gardner Museum, Boston*
[4]*Santa Fe Institute*

November 25, 2021

Abstract

This document provides additional information on the raw data and how we preprocessed it, how we estimate prior experience, a technical result on one of the econometric estimator, and several robustness checks.

Keywords: World War II; military procurement; learning curve; natural experiment.
JEL codes: 031; 038; N62.

*Contacts: francois.lafond@inet.ox.ac.uk, dsgreenwald@gmail.com, doyne.farmer@inet.ox.ac.uk.

Contents

A Data sources, data collection and data cleaning

A.1 The *Labor Productivity* dataset

The *Labor Productivity* data comes from three different sources Fig. 1 shows the times series (only the slopes are comparable, except for the Source Book data in which all series are expressed in person-hours per pound of aircraft).

Searle (1945). We extracted the data from Tables 1, 2, 3, 6 and 7. Victory and Cargo vessels are indices constructed from multiple models. A summary of the products we have information about is in the table below.

Product	Start date	End date	T	Total prod.
Liberty Ships	Dec-41	Dec-44	37	2458
Victory Ships	Feb-44	Dec-44	11	199
Cargo Vessels	Apr-43	Dec-44	21	160
Tankers Vessels	Jun-43	Dec-44	19	308
Destroyer Escort	Apr-43	Nov-44	20	351

Table 1: Ships data extracted from Searle (1945)

The Source Book. The report that provided Alchian with the data used in his study is available in the form of a digitized PDF[1]. To create this dataset, we transcribed Tables 3 and 4 in this report, *Source Book of World War II Basic Data - Airframe Industry, Volume 1: Direct Man-Hours - Progress Curves (Dayton, OH: Army Air Forces, Air Materiel Command, January 1950)* (Army Air Forces 1947) The *Source Book* presented significant transcription challenges. Some of the digits were illegible or had been clearly switched during the transcription process with digits similar in appearance, like an 8 for a 0. Luckily, Tables 3 and 4 represent the same data – person-hours per airframe pound and cumulative production – about the same models of airplanes. Table 3 organizes this data principally by manufacturer and plant, while Table 4 organizes it by airplane model. Therefore, the two tables could be compared to one another to corroborate interpretations of certain entries that were hard to read or seemed clearly wrong in one table or another. In the rare cases where it was impossible to transcribe the data faithfully after consulting both tables, we dropped the observations. In one case, the Consolidated Vultee San Diego B-24 August 1943 value for person-hours was changed from a clear 0.07 to a much more plausible 0.77 (the series read $\ldots 0.88, 0.84, 0.84, 0.07, 0.67, 0.65, 0.65 \ldots$).

The file gives value of cumulative production, from which we deduce production as the difference in cumulative production. In one case, the B-17 from Seattle, cumulative production was available at the earliest date, January 1940. The series reads

[1] https://apps.dtic.mil/dtic/tr/fulltext/u2/a800199.pd

45, 49, 54, ... Clearly, 45 was not the monthly production in January (see Mishina (1999)), so we just assumed that production in January was the same as in February, 4 units.

Finally, there is a page from Table 3 missing in the available PDF (page 42). Unfortunately, because of the organization of the PDF, it is impossible to know what data about which manufacturers was on this missing page.

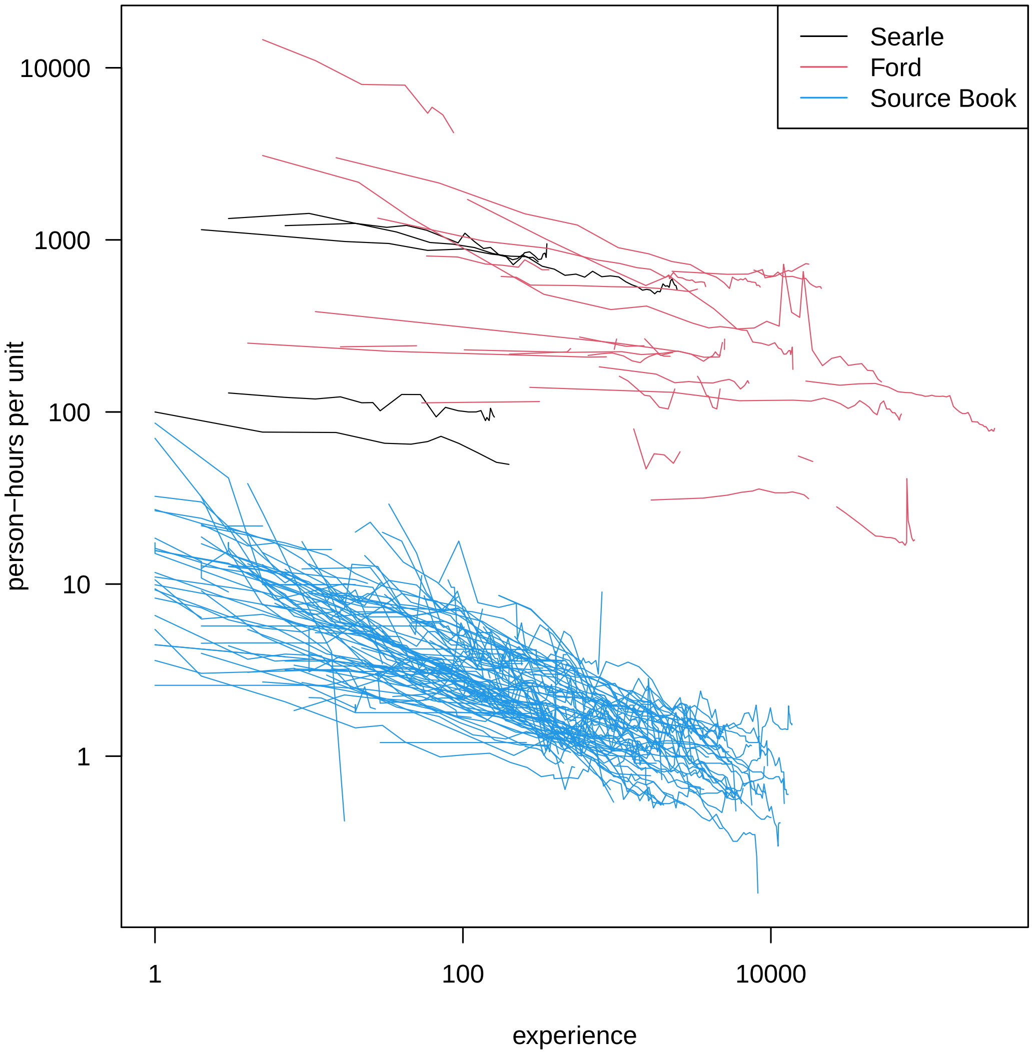

Figure 1: Time series of labor productivity from all included sources.

Table 2 shows some examples of aircraft-plant pairs from this source. We have chosen the examples to show that some plants produced multiple aircrafts, some aircraft were produced by multiple plants, and the total number of units produced and time span of production varied widely.

Ford Archival Records. The Ford Motor Company's archives are held in a dedicated research center, The Benson Ford Research Center in Dearborn, MI. In the Charles

Product	Start date	End date	T	Total prod.
B-17, Douglas, Long Beach	Oct-42	Jul-45	34	3666
B-17, Lockheed, Burbank	Jun-42	Jul-45	38	2750
C-69, Lockheed, Burbank	May-44	Sep-45	17	16
A-20, Douglas, Tulsa	Oct-44	Jun-45	9	1085
SB2A, Brewster, Johnsville and L.I.C.	Jan-43	May-44	17	302
R-5, Sikorsky, Bridgeport	Jan-45	Aug-45	8	11

Table 2: Examples of data extracted from the "Source Book"

La Croix papers, there is a copy of a publication called Record of War Effort: Contributions of the Ford Motor Company in the Development of Production for Victory (Detroit, MI: Ford Motor Company, n.d. 2 vol.). Volume 2 describes the monthly person-hours-per-unit requirements for what appears to be all of the products Ford produced throughout World War II. As this seems to have been an internal publication, there are no sources for this data beyond the implication that they are from extensive internal auditing and record keeping during the war. Table 3 summarizes the data extracted for Ford's archives.

A.2 The *OMPUS-USMH* dataset

This section presents detailed information about the two principal components of an original data set we assembled for this research: the *Official Munitions Production of the United States* and *United States Munitions Handbook*.

The PDF of the *Official Munitions Production of the United States* (OMPUS) is easily available[2], and contains data on production volume. This document is a Special Release, edited in 1947, covering each month from July 1940 ("the beginning of the war program") through August 1945 ("the last month of actual fighting against Japan"). Footnotes often make references to data being only a partial coverage, often because data from some component agencies was not available. In a few cases (experimental aircraft), we also have data from January to June 1940. This source was easy to read. We omitted Canadian data, and products with only one or two values of production. For ships, we took the value in displacement tons instead of units. For a few products, some of the data was available as aggregate for typically 6 months or a year. In these cases we attributed to each month a *pro rata* value.

The *United States Munitions Handbook* (USMH) is a formerly classified publication that was located in the Policy Documentation File (Record Group 179, Stack Group 570) by one of us (D.G.) on a research trip to the National Archives in College Park, MD in April 2015. The transcription from photographs of the document did not present any significant challenges. We note here that for airplanes, the cost data often appears to refer to particular plants, whereas the reference OMPUS production is product-level.

The USMH contains data on "early" and "late" cost for many products. These products are named, and a reference to the OMPUS is provided in the form a page

[2] http://cgsc.contentdm.oclc.org/cdm/ref/collection/p4013coll8/id/3332

Product	Start date	End date	T	Total prod.
Universal Carrier GAU	Mar-43	May-45	27	13893
Cargo Truck - OTBA	Jul-43	Oct-44	16	2218
CG-13A - Glider (42Places) - GBG	Jan-44	Dec-44	12	87
MX Engine Assembly	Sep-44	Jul-45	11	2378
Aircraft Generators – GAL P-1 and R-1	Dec-42	Jul-45	32	87390
British Engine – GAE	Jun-42	May-43	12	17593
British Axel – GAE	Jun-42	May-43	12	17639
Bomb Service GTBB	Apr-43	Sep-43	6	50
Bomb Service GTBC	Sep-43	Oct-44	14	4701
Cargo Truck - GTB (Less Winch)	Jun-42	Mar-43	10	5007
Stake Truck – G8T	Mar-43	Mar-44	13	7198
Cargo Truck - G8T	Sep-42	May-45	33	70420
Tank Engine GAA	Jul-42	Aug-45	38	21478
Turbo Supercharger - B2 and B22	Aug-42	Oct-44	27	52281
Bomb Service GTBS	Nov-42	Jul-44	21	4679
MX Field Assembly	Sep-44	Aug-45	12	2579
Jeep GP and GPW	Feb-41	Jul-45	54	283664
Tractor Truck G8T	Dec-43	Jan-44	2	314
Armored Car M-8 - GAK	Mar-43	May-45	27	8524
Cargo Truck - GTB (With Winch)	Jul-42	Mar-43	9	995
Tank Engine GAF	Nov-42	Sep-44	23	3908
Tank Engine GAN	Aug-43	Dec-44	17	380
Armored Car M-20 GBK	May-43	Jun-45	26	3773

Table 3: Data extracted from Ford's archives

and column number. This provided an uncontroversial match for the vast majority of products, although in some cases the USMH seems to refer to more models than the OMPUS. In a few cases, the match using the page and column number was erroneous, and we used names instead. In a few other cases, product detail was higher in the USMH than in the OMPUS, so that different cost changes were attributed to the same production time series. We did not transcribe these cases.

One specific issue with the matched OMPUS-USMH data is that the USMH does not provide a very clear definition of the cost data ("Standard Dollar Weight"). The Foreword to the USMH states: "The cost figures shown for the separate items are the standard costs which were used in computation of the War Production Board (WPB) index of war production and the Production Statement. They are included in this report to provide the reader with a proper perspective on the magnitude and relative significance of the items involved. Both an "early" and a "late" cost are shown wherever possible, comparison of the two costs oftentimes provides a clue to the tremendous advances in manufacturing techniques which took place in some munitions areas, enabling costs to be cut sharply even during a period of generally rising prices." In short, we think the Standard Dollar Weight represents a nominal dollar amount reported to understand product-level inflation over the course of the war. However, it could be that this is already deflated, so we chose not to deflate the data further in our main text analysis. We note that production in World War II was conducted in a climate of price controls and the rationing of materials and labor (Evans 1982). Despite this inflation was 5% in 1941, 10% in 1942 and averaged 6% annually for the remainder of the war (U.S. Bureau of Economic Analysis 2017).

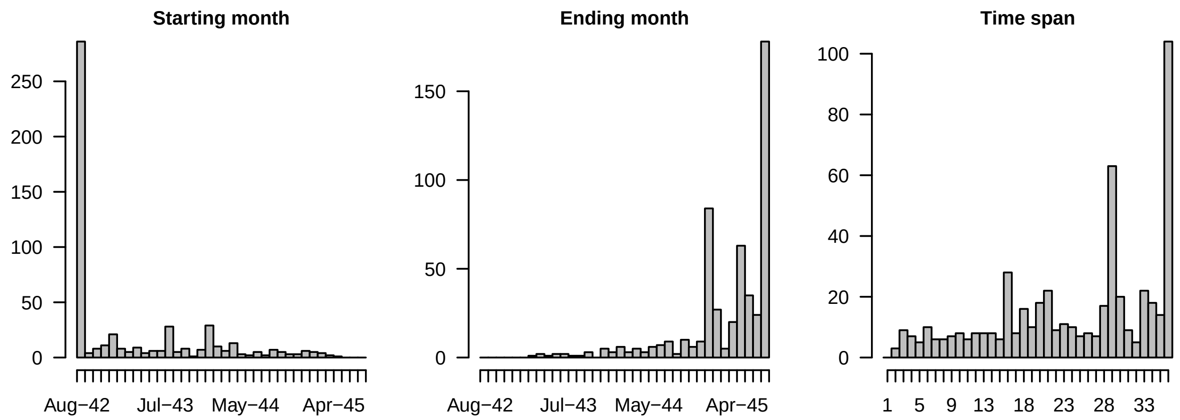

Figure 2: Distribution of the "early" month, "late" month, and number of months in between.

A second issue with the dataset is that we had to modify the dates with which the "early" and "late" costs are associated. While the dates of the early and late costs are reported for each product in the USMH, these dates are always the same in each product category. However, in the explanatory notes (e.g. USMH p.104, explanatory notes for Ordnance and Automotive Vehicles), an important clarification is that "the cost of the item as of the last month of production has been shown as the final cost, while for items produced after 1942, the dollar value shown for the earliest month of production has been listed as the original cost". Therefore, every time we found that a product was not yet in production at the date of early cost, we corrected the date of the early cost as the month in which production started. Every time we found a product for which production had stopped before the date of the late cost, we corrected the date of the late cost as the month in which production stopped[3]. Fig. 2 shows the distribution of the corrected Early and Late dates, as well their difference. For a large number of products we have a start date in August 1942 and an end date in August 1945, 36 months later.

Fig. 3 shows the USMH-OMPUS data (only the slopes are comparable, and "unit" costs may refer to units, pairs, thousands, or millions of units depending on the product).

[3]For 46 Ordnance items (OMPUS ref. 177/2 to 188/7) the Early date reported was the implausible April 1945, but the explanatory notes report that "The August 1942 cost was used as the original production cost for both Army and Navy items" so we edited this subset accordingly. For 341 products, the late date was September 1945 but our production data stops in August 1945, so we assumed that the Late cost was for August. For 2 products, production starts on the month of the "Late" date, so we removed them.

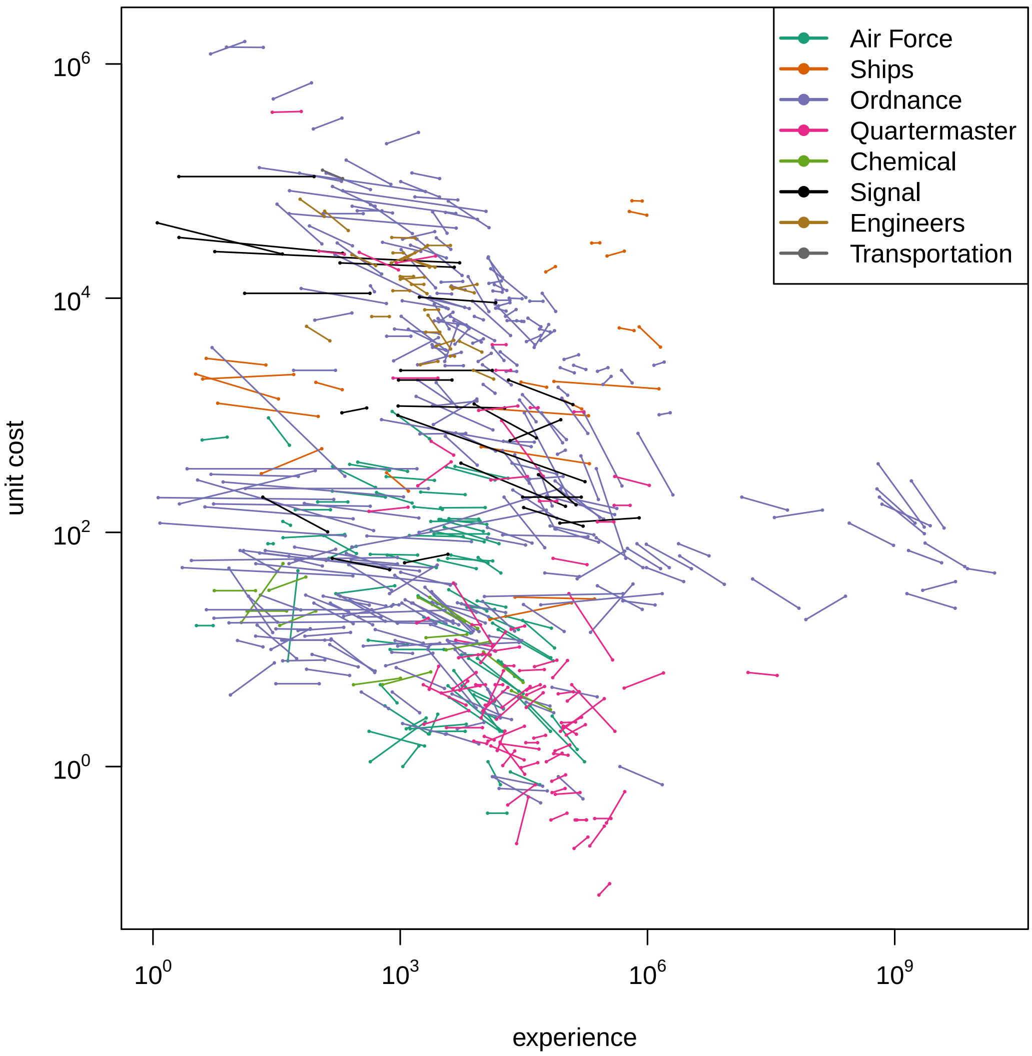

Figure 3: Experience curves constructed by matching USMH and OMPUS.

A.3 The *Contract Prices* dataset

We collected the *Contract Prices* data from Crawford & Cook (1952) (tables PR-2, PR-3 and PR-20), who compiled the estimated value of procurement from various sources, using a sample of products. "For many groups the sample covered more than 90 percent of the total values".

The production index was computed as follows: "Quantities of the sample items delivered each month were multiplied by a weighted unit cost for the item to derive the dollar value of the sample. The unit cost figure for each item was based on the contract or purchase price plus allowances for overhead, the cost of Government-furnished equipment and materiel and any other costs incurred in connection with the item by the War Department." Most importantly, these time series represent physical volume, not the product of physical volume and prices. The relevant excerpt from Crawford & Cook (1952) is footnote *a* on p. 20 "Data were computed from physical quantities delivered and standard dollar weights which for most items were unit costs as of 1945. The figures therefore reflect physical volume rather than cost to the Government; they do not take into consideration price changes or contract renegotiations." The explanatory notes on p.86 further state that "The series was designed to show relative magnitudes and trends in the physical volume of procurement deliveries" Fig. 4 shows the data on production, clearly exhibiting a plateauing in 1943-44 and decrease in 1945.

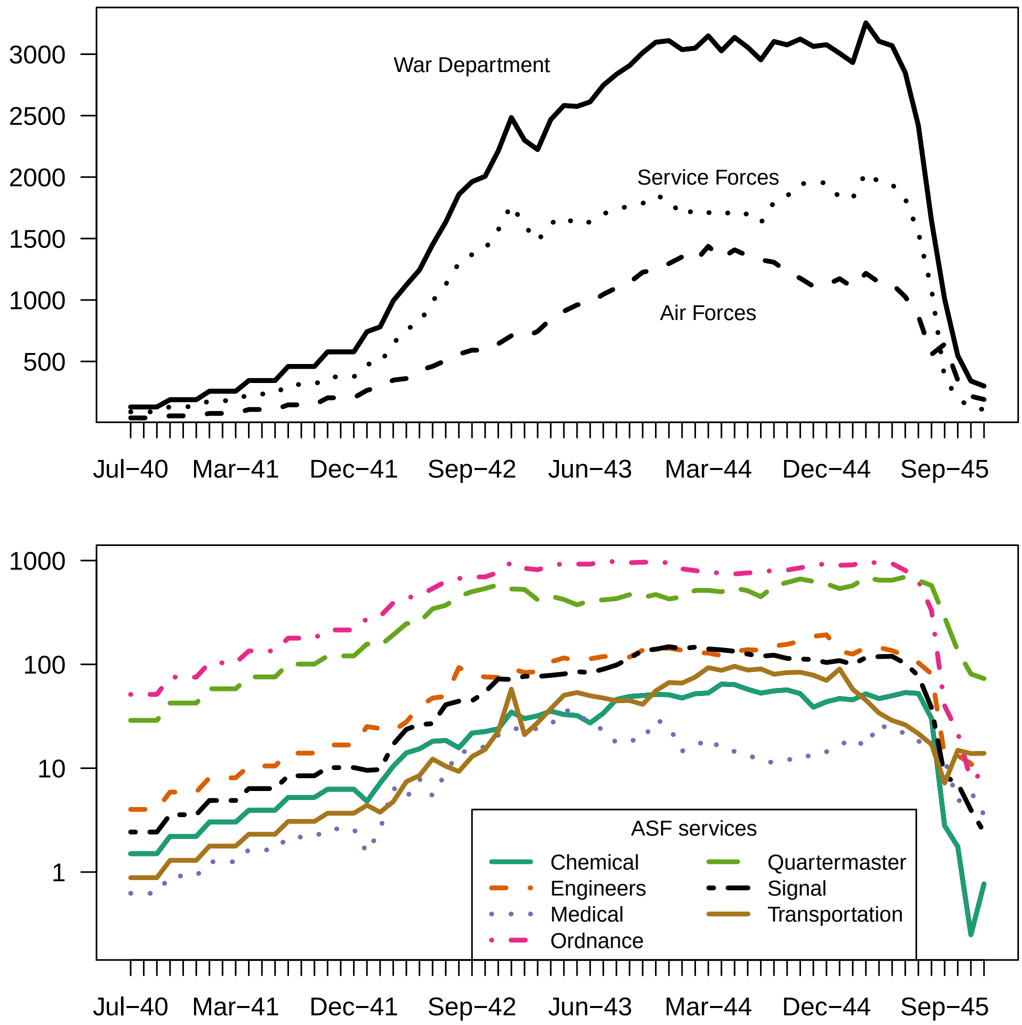

Figure 4: Estimated monthly rates of output between July 1st 1940 and July 31st 1945, total and by main category, in millions of standard dollar weights. Source: Crawford & Cook (1952).

The monthly data starts in January 1942 for all series. However, for the War department, the AAF and the aggregated ASF, quarterly data on production was available for the previous 6 quarters (1940Q3-1941Q4). Because this information is useful for constructing experience, we used it as follows. For these three series, we constructed monthly data for July 1940-December 1941 by attributing equally to each month the quarterly production data. For the subservices, we computed the share of each subservice in the ASF total for the first 6 months of 1942, and used these shares to calculate monthly production for the period July 1940-December 1941. Note that since price data starts in January 1942, these assumptions are only useful for plotting Fig. 4, and do not change our regression results. Similarly, the production data was not available for the last four months for AAF. We computed the ratio of AAF to ASF in the previous 6 months (March to August 1945), and used this to estimate the values for AAF, and thus for the Total War department as well, for September-December 1945.

The indices of contract price changes were computed as follows: "The items included in these indices cover approximately 50 percent of the total value of War Department procurement. They were selected to be representative of all principal kinds of items purchased. The basic data employed were the contract prices for each company supplying the item on the selected list. All successive prices in additional contracts or revisions of existing contracts were recorded after necessary adjustments were made for specification changes. The price data for all companies supplying a given item were used to compute an index for that item after appropriate weights had been assigned on the basis of relative importance in terms of physical volume".

The explanatory notes also mention that "Individual item indices were combined into group indices and, in turn, into technical service indices. These composites were combined into a master Army Service Forces (ASF) Index, and a similar composite index on Army Air Forces (AAF) items was added to the Army Service Forces composite to provide a War Department index. The indexes do not cover any items produced in government-owned contractor operated plants, or, with the exception of the AAF index, items procured through cost-plus-a-fixed-fee contracts since such purchases were to a degree noncompetitive and the contract terms were often such as to cause the prices to be, incomparable with those of procurement through ordinary commercial channels." Fig. 5 shows the price indices for contract for various wartime agencies, indicating an important decrease for almost every department, the exception being the Quartermaster.

B Estimating prior experience

Estimating relevant prior experience for each of the product categories included in our datasets was one of the greatest challenges we faced in writing this paper. In order to create these estimates, we made a couple of assumptions about prior experience. First, we assumed that Americans gained most of their experience in producing military-specific products (guns, munitions, etc.) during World War I. Therefore, we were able to use the extensive statistical and primary sources available about WWI output to create these estimates. Second, where a technology had both military and civilian applications, we aggregated the WWI military output and rarer estimates of civilian output, where possible. For civilian production, two sources were essential: *the Historical Statistics of the United States* and history of science and technology books about specific products such as radios and airplanes.

The OMPUS data is far more granular than the contract price data. Therefore, after estimating initial experience for products included in the OMPUS data (Section B.1), we present a crosswalk that aggregates the OMPUS-level estimates and matched them

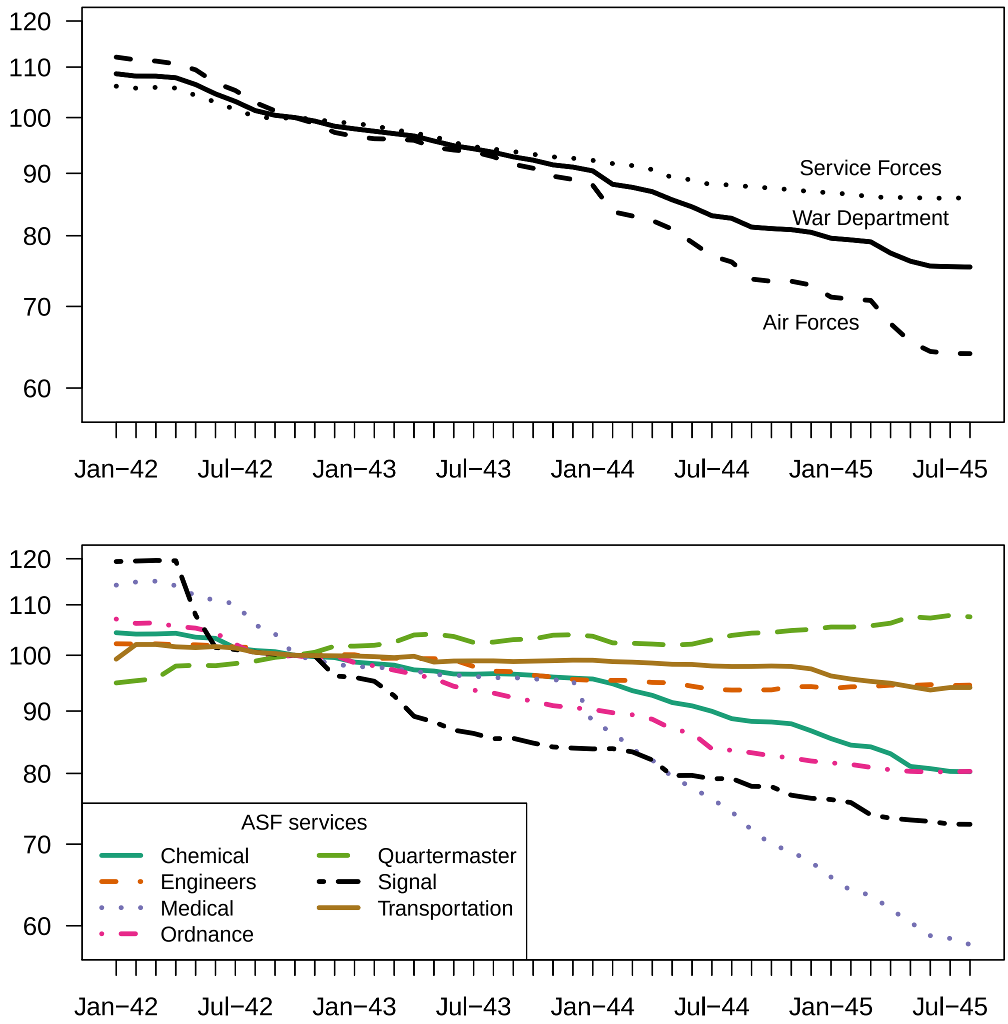

Figure 5: Quarterly Index of Contract Price Changes: 1942 - 1945 for War Department and Component Agencies (October 1942 = 100). Source: Crawford & Cook (1952).

to the categories in the contract price data (Section B.2).

Main categ.	Subcateg.	ζ	N	War Dep.
Aircraft	Bomber	0.21	15	Air Force
Aircraft	Fighter	0.21	12	Air Force
Aircraft	Reconnaissance (inc. Photographic)	0.21	1	Air Force
Aircraft	Transport	0.21	8	Air Force
Aircraft	Trainer	0.21	4	Air Force
Aircraft	Communication	0.21	3	Air Force
Aircraft	Special Purpose Aircraft	0.21	0	Air Force
Aircraft	Gliders	0.21	0	Air Force
Aircraft	Airships, Barrage Balloons, and Special Devices	0.21	0	Air Force
Aircraft	Aircraft Engines	0.21	21	Air Force
Aircraft	Aircraft Propellers	0.21	12	Air Force
Ships	Combatant	1.21	7	Ships

Ships	Landing vessels	0.05	5	Ships
Ships	Patrol	0.75	3	Ships
Ships	Mine Craft	0.81	1	Ships
Ships	Transports	0.05	0	Ships
Ships	Dry Cargo	0.05	0	Ships
Ships	Tankers	0.05	0	Ships
Ships	Tender and Repair Vessels	0.05	1	Ships
Ships	District Craft	0.05	1	Ships
Ships	Other	0.05	3	Ships
Ships	Maritime Commission Nonmilitary Vessels Delivered to the Armed Forces	0.05	0	Ships
Ships	Army Tugs and Barges	0.05	0	Ships
Ordnance	Field Artillery	0.39	12	Ordnance
Ordnance	Spare Canon, Tubes, and Recoil Mechanisms for Field, Tank, and Self-Propelled Artillery	0.40	0	Ordnance
Ordnance	Tank Guns and Howitzers	0.40	0	Ordnance
Ordnance	Self-Propelled Guns and Howitzers	0.40	6	Ordnance
Ordnance	Aircraft and Army Antiaircraft Guns	0.40	8	Ordnance
Ordnance	Army Rocket Launchers	0.40	6	Ordnance
Ordnance	Mortars	0.40	4	Ordnance
Ordnance	Naval Surface Fire (Guns and Small Arms)	0.40	4	Ordnance
Ordnance	Naval Antiaircraft and Dual-purpose (Guns and Small Arms)	0.40	6	Ordnance
Ordnance	Naval Rocket Launchers	0.40	0	Ordnance
Ordnance	Small Arms	0.40	18	Ordnance
Ordnance	Misc. Army Weapons and Ordnance Mat.	0.40	10	Quartermaster
Ordnance	Misc. Navy Weapons and Ordnance Mat.	0.40	0	Ordnance
Ordnance	Fire Control (excl. radar)	0.40	14	Ordnance
Ordnance	Artillery and Tank Gun	0.35	61	Ordnance
Ordnance	Aircraft (Ammunition)	0.35	7	Ordnance
Ordnance	Army Antiaircraft	0.35	6	Ordnance
Ordnance	Mortar Shells	0.35	13	Chemical
Ordnance	Army Rockets	0.35	6	Ordnance
Ordnance	Army Practice and Drill (All Types)	0.35	3	Ordnance
Ordnance	Naval Surface Fire (Ammunition and Bombs)	0.35	8	Ordnance
Ordnance	Naval Antiaircraft and Dual-purpose (Ammunition and Bombs)	0.35	4	Ordnance
Ordnance	Navy Rockets	0.35	0	Ordnance
Ordnance	Small Arms Ammunition	0.35	15	Ordnance
Ordnance	Land Mines	0.10	0	Ordnance
Ordnance	Grenades	0.10	0	Ordnance
Ordnance	Pyrotechnics	0.10	0	Chemical
Ordnance	Explosives	0.10	0	Ordnance
Ordnance	Propellants : Smokeless Powder	0.10	0	Ordnance
Ordnance	Torpedos	0.10	1	Ordnance
Ordnance	Naval Mines	0.10	1	Ordnance
Ordnance	Depth Charges	0.10	1	Ordnance
Ordnance	Aircraft Bombs	0.00	31	Ordnance
Ordnance	Combat Vehicles (Tanks)	0.01	6	Ordnance
Ordnance	Motor Carriages for Self-propelled Guns	1.00	1	Ordnance
Ordnance	Heavy-heavy Trucks	1.99	17	Ordnance
Ordnance	Light-heavy Trucks	1.99	10	Ordnance
Ordnance	Medium trucks	1.99	5	Ordnance
Ordnance	Light Trucks	1.99	3	Ordnance

Ordnance	Trailers, Semitrailers, and Motorcycles	1.99	2	Ordnance
Ordnance	Remanufactured Automotive Vehicles	1.99	0	Ordnance
Ordnance	Tractors	1.99	8	Ordnance
Comm.	Army (Radio)	0.04	5	Signal
Comm.	Navy (Radio)	0.04	0	Signal
Comm.	Ship and Ship-and-Shore (Radio)	0.04	0	Signal
Comm.	Ground (Radio)	0.04	7	Signal
Comm.	Army (Radar)	0.00	4	Signal
Comm.	Navy (Radar)	0.00	0	Signal
Comm.	Ship and Ship-and-Shore (Radar)	0.00	0	Signal
Comm.	Ground (Radar)	0.00	3	Signal
Comm.	Underwater Sound Equipment	0.00	0	Signal
Comm.	Wire Communication and Misc. Equipment	0.10	4	Signal
Other	Petroleum Products: Aviation Gasoline	0.20	0	Air Force
Other	Machinery	1.00	27	Engineers
Other	Railroad Equipment	1.00	1	Transportation
Other	Clothing	1.00	50	Quartermaster
Other	Medical Supplies and Subsistence Rations	0.10	0	Medical
Other	Misc. Equipment and Supplies	0.50	28	Quartermaster

Table 4: Estimated prior experience for *OMPUS-USMH* data. Main and Subcategory are the main section and finest available subsection of the OMPUS table of contents (ToC); N is the number of products; War Department is from our hand-made crosswalk. Horizontal lines delineate the higher-level ToC categories discussed in the text. Note that product types for which we have no data matched with USMH ($N = 0$) are also reported.

B.1 Estimates of prior experience for the *OMPUS-USMH* data

This appendix provides an explanation for how we arrived at an estimate of prior experience for each category of product in Table 4. The total wartime production for each category was taken from the summary table "Production of Selected Munitions Items" in War Production Board (1945). As discussed in Section *Data* in the main text, the OMPUS dataset disaggregates many products into their component parts. The aggregate table in War Production Board (1945) sums these components into larger product categories and then industry-level categories. We have used this table in lieu of summing the OMPUS ourselves to avoid mismatching components of the same finished product. This appendix explains how we gathered numbers about prior production and wartime production to calculate the prior experience factor ζ_is presented in table 4.

Aircraft. Aircraft were not a novelty in World War II, but the scale and methods of manufacture changed significantly during the war. Furthermore, significant changes were made to their design. Much of this change was linked to improvements in engines and propellers, which are a separate category in the OMPUS dataset and are discussed below. However, the United States did have prior experience in manufacturing aircraft – major firms like Boeing and Curtiss (now Curtiss-Wright) were both founded in 1916. Therefore, we estimated this prior experience by finding the number of individual civil and military airplanes produced in the United States before 1940. Consulting Pattillo (1998) and Lorell (2003), we were able to determine that 62,401 aircraft were produced in the United States before World War II. Many of these aircraft were produced for World War I and for the postal service, which used planes to transport mail over long distances. According to the War Production Board (1945), 296,429 aircraft were produced during World War II. We thus applied a value of $\zeta_i = 0.211$ to all types of aircraft.

Aircraft Engines and Propellers. As mentioned, the OMPUS often disaggregates products into their components. Therefore, it provides cost and production information not only for airframes and completed airplanes, but also separate information for airplane engines and propellers. If we assume that each aircraft built prior and during the war used two engines and two propellers, the estimate of ζ_i remains the same as for aircrafts, $\zeta_i = 0.21$. We note that it may be an overestimate, because unlike for the construction of airframes and other components, there were design changes made to aircraft engines during the war that made prior manufacturing experience less relevant than it was to other areas of aviation. For example, automotive firms with no prior aviation manufacturing experience were asked to adapt the Rolls Royce Merlin piston engine for mass production (Hyde 2013). Other firms, notably Pratt & Whitney, had extensive experience manufacturing piston engines (the type of engine used in the majority of WWII planes) for aircraft. However, the most commonly used types of engines in World War II like the Pratt & Whitney R-2800, were only designed in 1937 and flown for the first time in 1940. (Connors 2010). Other commonly used engines, like the Wright R-3350 used for the famous B-29 bomber, were developed around the same time (LeMay & Yenne 1988). Therefore, while engines were not totally novel at the outbreak of war, they were not fully mature products; furthermore, new designs and changes for mass production were common (White 1995).

Ships. There were two principal categories of ships produced in WWII: transport vessels created for the Maritime Commission and warships made for the Navy.

The Liberty Ships created for the Maritime Commission have been much studied (Thornton & Thompson 2001, Thompson 2001, 2007, 2012). The War Production Board (1945) table states that 53 million deadweight tons of cargo ships were manufactured in WWII. As Thompson documented, there was little pre-war experience in the manufacture of transport ships. 2.7 million deadweight tons of cargo ships were made during the First World War (Ayres 1919). We used $\zeta_i = 2.7/53 \approx 0.05$ for all ships except combatant ships.

We used several different sources for the warships. The first was George (n.d.), which showed that the U.S. had 297 warships at the end of World War 1. The second were the naval treaties agreed upon by the Great Powers during the 1920s and 30s [4]. In addition, we used Roosevelt's 1938 "Message to Congress Making Recommendations for Defense" [5] to work out the number of larger ships built after the treaties lapsed, which showed the numbers of larger ships produced between World War I and World War II. The third was the Dictionary of American Naval Fighting Ships [6], which

[4] These were the Washington Treaty and the First and Second Treaties of London

[5] https://www.mtholyoke.edu/acad/intrel/interwar/fdr11.htm

[6] https://www.hazegray.org/danfs/

showed the number of smaller ships and submarines the US produced from the end of World War 1 to the end of 1942. The fourth was the US Navy's Naval Heritage and History Command's record of the size of the US Navy over time [7], which showed the number of each class of ship produced over the course of World War II. Combatant ships are battleships, carriers, escort carriers, cruisers, destroyers, frigates (or 'escort destroyers' as they were called at that time), and submarines. From the sources, we calculated that 889 combatant ships were produced before the war, and 733 during the war. Hence, we used $\zeta_i = 889/733 \approx 1.21$ for combatant ships. From the final source, we calculated the number of landing vessels, patrol boats, and mine craft produced before and after the war. There were 121 landing vessels produced before the war, and 2426 produced during the war. Hence, we used $\zeta_i = 121/2426 \approx 0.05$ for landing vessels. There were 515 patrol boats produced before the war, and 689 produced during the war. Hence, we used $\zeta_i = 515/689 \approx 0.75$ for patrol boats. There were 263 minelayers and minesweepers produced before the war, and 323 produced during the war. Hence, we used $\zeta_i = 263/323 \approx 0.81$ for mine warfare.

Guns and Small Arms. While the production of planes continued for civilian consumption during peacetime in the interwar period, the production of weaponry like guns and small arms slowed significantly between the wars. As stated in Herman (2012), the U.S. army shrunk to being only the 18th largest army in the world before World War II. We exploit this fact to use weapons produced during World War I as our proxy for prior experience manufacturing guns, small arms, ammunition and bombs.

Drawing on information from Broadberry & Harrison (2005) and primary source material from Ayres (1919), we were able to estimate the production of a variety of artillery and guns during World War I. For example, there were 3,077 complete units of artillery equipment manufactured, 226,557 machine guns, 3.43 million rifles and 1.7 million pistols and revolvers. The respective numbers for each of these categories produced during World War II were 7,803 artillery units ($\zeta \approx 0.39$), 2.68 million machine guns ($\zeta \approx 0.08$), 6.5 million rifles ($\zeta \approx 0.53$) and 2.74 million pistols and revolvers ($\zeta \approx 0.621$). Based these ratios, and for simplicity, we assume $\zeta_i = 0.4$ for all items in this category.

Ammunition and General Purpose Bombs. The numbers of ammunition and general purpose bombs produced in World War I were available from the same sources. In World War I 20.3 million artillery rounds were produced and 3.5 billion rounds of ammunition for rifles, revolvers and other small arms. In World War II these numbers were 33.5 million ($\zeta \approx 0.61$) and 41.5 billion ($\zeta \approx 0.08$) respectively. We used $\zeta \approx 0.35$ in these categories.

It is slightly harder to match numbers for conventional bombs. However, we know that 132 million pounds of "high explosives" – an essential component for all bombs – were produced during World War I. While it is hard to do a clear match of this explosive component to the reported weight of bombs in the War Production Board (1945)

[7] https://www.history.navy.mil/research/histories/ship-histories/us-ship-force-levels.html

table, the closest category reported – "Aircraft bombs (Army and Navy), General Purpose and Demolition" – states that 7.1 billion pounds of bombs were produced, suggesting $\zeta \approx 0.02$. Acknowledging that this seems very low, our choice of the prior experience coefficient for this category is 0.1.

Aircraft bombs, Not General Purpose. The secondary literature generally agrees that there was almost no production of incendiary or fragmentation bombs during World War I, and no testing of this materiel between the wars. Therefore, we can assume prior experience of almost 0 for these models of explosives (Ross 2003, Hecks 1990). According to the War Production Board (1945) table, there were 2.26 million incendiary, fragmentation and armor-piercing bombs produced. We used $\zeta = 0.001$.

Combat and Motor Vehicles. This category unites products that were similar to products that U.S. manufacturers were already producing, such as jeeps and trucks, with others, like tanks, for which they had almost no prior experience. We were able to find disaggregated numbers for many of these products. For example, we know that prior to 1940 a cumulative number of 4.89 million trucks were registered in the United States (Cain 2006). During the war, 2.45 million trucks were manufactured, both for use on the front and for the armament effort at home, suggesting a $\zeta \approx 1.99$. In contrast, prior experience in manufacturing tanks was very low. Only 799 tanks were produced during World War I and there was no military demand for further production in the interwar period (Ayres 1919). During World War II, 86,333 tanks were produced. Since apart from tanks, all products in this category are similar to trucks, we use a category-level $\zeta = 1.99$, except for one product in the "Motor Carriages for Self-propelled Guns" category, which is a light tank chassis, for which we used $\zeta = 1$.

Communications and Electronics. Similar to Combat and Motor Vehicles, this category groups together products that manufacturers had a wide range of experience producing. In particular, there is a clear distinction between radios and radar. Radios were extensively manufactured prior to World War II, primarily for civilian and commercial use. Approximately 86,400 radio sets had been produced by U.S. manufacturers by the end of 1940 (Cain 2006). In stark contrast, only 22 radars had ever been made globally prior to 1940. Only the British "Chain Home" system was operational before 1940, with the first stations opening in 1938. Therefore, we apply prior experience corrections at the product level. Furthermore the table in *War Production Achievements* that we use for aggregate production numbers does not report communications and electronics output in terms of individual units, but rather in dollar values. Therefore, exceptionally for this category, we have summed cumulative production stated in Crawford & Cook (1952). According to this aggregation, 940,852 ground radio sets were manufactured, including vehicular radios, plus 1.25 million air radios were manufactured ($\zeta \approx 0.04$). Just over 66,000 radar sets were completed for ground and airborne use, suggesting truly negligible prior experience. (This number excludes the transponders and fuses that were attached to American materiel for friend-or-foe recognition.). We applied the above-mentioned experience factors for radar and radios, the same as radar for underwater sound equipment, and $\zeta = 0.1$ for products in the "Miscellaneous wire communication" category, mostly wires and cables.

Other Supplies. This is a broad category that unites products used to outfit, house, feed and provide medical treatment for soldiers, as well as machinery and construction equipment. Prior experience varied greatly for these products,

In textiles and household-like goods, such as clothing, tents and cannisters, U.S. manufacturers had extensive prior experience. A priori, WWII military production of clothing compared to previous clothing produced should be small, suggesting a very high ζ. It was surprisingly difficult to find estimates of prior production denoted in units (rather than dollars) for these categories. Therefore, we have to use very rough estimates of prior production from Carter et al. (2006) to estimate prior experience in this category of products. This series allows us to estimate numbers for manufactured apparel, specifically men's and boys suits and coats, back to 1927. In total, 178,496,000 of these items of clothing were produced from 1927 to 1940. This gives a lower bound to be compared with the 428,316,000 items of clothing (not including socks) manufactured for soldiers and sailors during the War, suggesting $\zeta = 0.41$. Since this is clearly lower bound, we assume $\zeta = 1$.

For aviation gasoline, we used the same estimate as for aircraft, $\zeta = 0.2$.

The Machinery category includes mostly construction equipments, such cranes, showels, road rollers, and road scrapers, and railroad equipment includes one model of locomotive. Assuming that prior experience was probably lower than for trucks and automobile (2), but higher than for most other products, we chose $\zeta = 1$.

The miscellaneous equipment categories includes everything from sleeping bags to airplane hangers, through insecticide and steel drums. Overall they tend to be items for which there existed significant prior experience, and we chose $\zeta = 0.5$.

Medical supplies and medicines–like morphine, penicillin, sulfa drugs and plasma–were mass produced for the first time during World War II (Rostker 2013). Therefore, we estimate prior experience for this sub-category to be very low–1% of WWII output. The total output of these products during World War II was 6 billion ampules. We assumed an experience correction factor of 10% because the category including Medical Supplies also includes subsistence rations. Note that we have no product for this category in the OMPUS data,but we will use this estimated prior experience in the Contract Prices dataset,using a procedure which we now explain in details.

B.2 Estimates of prior experience for the *Contract Prices* data

To obtain estimates of prior experience at the level of War departments/Army Service Forces, we take advantage of the fact that we have already justified prior experience coefficients at a lower aggregation level in the previous section. We manually construct a concordance table between each sub-category of the OMPUS Table of Content (ToC) and the War department services (see Table 4). We rely on Crawford & Cook (1952), the source of the War department data, where for each War department there is also a finer grained decomposition for the quantity of individual goods in each War

Department. We compared the items in these finer grained data to the OMPUS categories, and assigned an OMPUS category to a War Department if the goods that War Department procured matched the OMPUS category. In the cases where multiple department procured the same good, we assigned it to the department that procured the most of the good. We also supplemented this by consulting extensive histories of the divisions from the Army and military historians (Coates Jr 1959, Coker & Stokes 1991, Crawford & Cook 1952, Killblane 2012, Mauroni 2015, Risch 2014, Rubis 2012). For example, we assigned the 'mortar shells' category to 'Chemical', as Crawford and Cook list the 'Chemical' department as procuring the majority of mortar shells.[8]

War department	ζ	Z_0	Method
ASF Chemical	0.2	353	Our assumption
ASF Engineers	0.75	3774	Our assumption
ASF Medical	0.1	81	Average of corresponding OMPUS categ.
ASF Ordnance	0.6158	22437	Average of corresponding OMPUS categ.
ASF Quartermaster	0.6333	14561	Average of corresponding OMPUS categ.
ASF Signal	0.0259	106	Average of corresponding OMPUS categ.
ASF Transportation	1	2112	Average of corresponding OMPUS categ.
ASF Total	0.5931	43423	Sum of sub-services
AAF Total	0.2096	9421	Average of corresponding OMPUS categ.
Total War Department	0.4472	52845	Sum of sub-departments

Table 5: Estimated prior experience for the *Contract Prices* data

We computed the prior experience coefficient of a War Department as the average of the prior experience coefficient of its associated OMPUS ToC sub-categories. We thus obtained prior experience coefficients for the AAF and for 5 of the ASF subcategories. For the categories ASF Chemical and ASF Engineers, we somewhat arbitrarily assign the values 0.2 and 0.75, based on our reading of the historical literature.

To get an estimate of prior experience for the aggregate services ASF, we sum up the estimated prior experience of the corresponding subservices. The top part of Table 5 reports the estimated values of prior experience Z_0 for the ASF subservices. We sum up these values to obtain Z_0 for ASF Total. The table reports the corresponding value of ζ for information only, we do not use it to estimate Z_0. We proceed similarly to estimate Z_0 for the Total War department, which is the sum of ASF's and AAF's Z_0.

B.3 Estimates of prior experience for the *Labor Productivity* data

The *Labor Productivity* productivity data is mostly at the plant (Source Book) or product level (Ford, Searle) . There is an issue with correcting this data for prior experience

[8] Sometimes our mappings are unintuitive due to quirks in how the US procured goods. For example the $M2$ mortars the US used were originally designed to only fire smoke shells as the US peace lobby opposed the use of high explosives and chemical shells after WWI. Hence the Chemical department dealt with the ammunition. But during WWII they adapted them to fire high-explosive ammunition. Thus the Chemical department handled all types of ammunition, even though it was mainly high-explosives and thus seems more likely to be handled by Ordnance.

because if a plant enters in production late, it will not produce a lot and since the factor ζ is applied to total plant-level production, plants that arrive late and benefit most from past experience actually get a lower estimated prior experience. We decided to apply no correction to the data presented in the main text. See Appendix D.4 for the results when we apply a correction for initial experience.

C Estimators for the *OMPUS-USMH* dataset

In the *OMPUS-USMH* dataset, there are two observations per product, but the dates and span of these observations differ across products. Thus, we cannot estimate a *first*-differences model. In this appendix we discuss the "heterogenous-differences" (HD) model, in which we regress the differences in log cost on the differences in log experience and the time span between the two observations (and where no constant is allowed). We show that it results in the same regression coefficients as the fixed-effects (FE) model used in subsection *OMPUS-USMH: unit costs at the product level* of the section *Empirical results*, but that it is different from the cross section regression of the product's average monthly growth rates. We also discuss how the share of cost decrease due to the exogenous time trend is computed is Section *Discussion*.

Equivalence between the point estimates of the HD and FE estimators We define the Heterogenous Differences (HD) estimator as follows. For each individual i, there are two periods t_{0i} and t_{1i}, and we denote the span of time between the two as

$$t_{1i} - t_{0i} = \tau_i.$$

We define the HD operator Δ^{τ_i} on a variable V as the difference of the two available observations

$$\Delta^{\tau_i} V = V(t_{1i}) - V(t_{0i}).$$

Obviously,

$$\Delta^{\tau_i} t = t_{1i} - t_{0i} = \tau_i,$$

and

$$\Delta^{\tau_i} \text{constant} = \text{constant} - \text{constant} = 0,$$

so that applying the operator Δ^{τ_i} to our main equation

$$\log c_{i,t} = \text{constant} + \alpha t + \beta \log Z_{i,t} + \epsilon_{i,t}$$

gives

$$\Delta^{\tau_i} \log c_i = \alpha \tau_i + \beta \Delta^{\tau_i} \log Z_i + \Delta^{\tau_i} \epsilon_i \tag{1}$$

Note that just like in first differencing, applying the Δ^{τ_i} operator leads to the loss of one observation. Since there are two observations per individual to start with, there is now only one observation per individual, so we have removed the subscript t. Note also that there is no intercept in Eq. 1.

We define the HD estimator as the OLS estimator of Equation 1,

$$\hat{\beta}_{HD} = (X^T X)^{-1} X y, \tag{2}$$

where $y = \Delta^{\tau_i} \log c_i$ and, denoting τ_i as x_{i1} and $\Delta^{\tau_i} \log Z_i$ as x_{i2},

$$\underset{n\times 2}{X} = \begin{bmatrix} x_{11} & x_{12} \\ x_{21} & x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{bmatrix}$$

To show that it is equivalent to the Fixed Effects estimator, we observe that when there are only two observations, the "within" transformation is almost equivalent to applying the Δ^{τ_i} operator. The within transformation consists in substracting the group-specific mean from each observation, that is, for a variable V with two observations in t_1 and t_0, the within transformation operator $\mathcal{W}$ gives

$$\mathcal{W}(V(t_{1i})) = V(t_{1i}) - \frac{V(t_{0i}) + V(t_{1i})}{2} = \frac{V(t_{1i}) - V(t_{0i})}{2} = \frac{\Delta^{\tau_i} V_i}{2}$$

and similarly

$$\mathcal{W}(V(t_{0i})) = -\frac{\Delta^{\tau_i} V_i}{2},$$

so the within and HD transformations are very similar. But in contrast to the HD transformation, the within transformation does not reduce the number of observations, so a direct comparison of the matrix of regressors is not possible. However, we can write the within estimator as

$$\hat{\beta}_{FE} = (\tilde{X}^T \tilde{X})\tilde{X}\tilde{y}, \tag{3}$$

where

$$\underset{2n\times 2}{\tilde{X}} = \frac{1}{2} \begin{bmatrix} x_{11} & x_{12} \\ -x_{11} & -x_{12} \\ x_{21} & x_{22} \\ -x_{21} & -x_{22} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \\ -x_{n1} & -x_{n2} \end{bmatrix}.$$

Now, if we compute the entries of $X^T X$ and $\tilde{X}^T \tilde{X}$, we find $\tilde{X}^T \tilde{X} = \frac{1}{2} X^T X$ and thus

$$(\tilde{X}^T \tilde{X})^{-1} = \left(\frac{1}{2} X^T X\right)^{-1} = 2(X^T X)^{-1}. \tag{4}$$

Similarly, writing down explicitly the entries of $\tilde{X}\tilde{y}$ and simplifying shows that

$$\tilde{X}\tilde{y} = \frac{1}{2} X y \tag{5}$$

Putting Eqs. 5 and 4 into 3, and comparing with Eq. 2, we see that

$$\hat{\beta}_{FE} = \left(2(X^T X)^{-1}\right)\left(\frac{1}{2} X y\right) = (X^T X)^{-1} X y = \hat{\beta}_{HD}.$$

■

Non-equivalence between the HD and the growth rates cross-section estimators. When faced with heterogenously spaced data with two observations per individual, another option would simply be to calculate average growth rates, and perform a cross-sectional regression, that is

$$\frac{\Delta^{\tau_i} \log c_i}{\tau_i} = \alpha + \beta \frac{\Delta^{\tau_i} \log Z_i}{\tau_i} + \text{noise}. \tag{6}$$

As can readily be seen by comparing the matrix of regressors, the coefficients estimated from Eq. 6 and the HD/FE estimator Eq. 1 are in general different, so Table 4 in the main text (columns 4-6) also reports the estimates based on Eq. 6.

Share of cost decrease accounted for by the exogenous time trend To do a growth decomposition for the *OMPUS-USMH*, we take expectations of Eq. 1,

$$E[\Delta^{\tau_i} \log c_i] = \alpha E[\tau_i] + \beta E[\Delta^{\tau_i} \log Z_i],$$

so that the relative contribution of the exogenous time trend to the change in cost is estimated as

$$\text{share exo} = \frac{\alpha \frac{1}{n} \sum_i \tau_i}{\frac{1}{n} \sum_i \Delta^{\tau_i} \log c_i} \tag{7}$$

D Robustness checks

D.1 Time series analysis

We can perform time series analysis only in the *Labor productivity* and *Contracts* datasets, and they have different structures (unbalanced and $N > T$ for the first, but balanced and $T > N$ for the second).

Thus we first present results that relate to the time aspect of the models and that can be computed on all three datasets: two-way fixed effects, and using the lag (instead of contemporaneous) experience as regressor. We then proceed to discuss time series properties in the *Labor productivity* and *Contracts* datasets in turn.

We omit the specifications with production as a regressor.

Two-ways fixed effects In the main specification, we constrain the effect of the time variable to be an exponential trend. Instead, we can estimate a fixed effects model with both individual and time dummies, that is

$$\log c_{it} = \kappa_i + \theta_t + \beta \log Z_{it} + \eta_{it}. \tag{8}$$

This allows us to control for economy-wide (in addition to product-specific) effects on costs that are not necessarily growing exponentially in time. Table 6 reports the results[9], showing an estimate of the effect of experience similar to the one obtained with individual dummies and an exogenous linear time trend.

[9] The models are estimated by performing a single transformation (removing individual means) and adding time dummies, and the R^2 are the R^2 of this regression.

Table 6: Panel regression results for Two-ways fixed effects

	Labor Productivity	USMH	Contracts
Experience	-0.300***	-0.059**	-0.167*
	(0.018)	(0.020)	(0.058)
Observations	3034	1046	308
R^2	0.789	0.250	0.803

First lag of experience We use the first lagged value of experience instead of contemporaneous experience as a regressor. The results, presented in Table 7, do not change much as compared to the baseline results, except for the FD estimator in the Labor Productivity dataset where the experience coefficient drops by a half and the exogenous time trend instead increases. The coefficient for experience in the *OMPUS-USMH* is also somewhat weaker than in the baseline results.

Table 7: Panel regression results for Experience lagged 1 period

	Labor Productivity		USMH	Contracts	
	FE	FD	FE	FE	FD
Experience(t-1)	-0.236***	-0.109***	-0.033**	-0.149*	-0.120*
	(0.019)	(0.020)	(0.013)	(0.051)	(0.045)
Time	-0.008**	-0.036***	-0.005***	-0.003	-0.004
	(0.003)	(0.004)	(0.001)	(0.003)	(0.003)
N	2912	2719	1046	308	301
R^2	0.717	0.046	0.159	0.786	0.060

Labour productivity We first test the null of no first-order autocorrelation in the Fixed Effects results using experience and time as regressors (Second column of Table 3 in the main text), using Wooldridge's (2002) (section 10.5.4) test, and strongly reject it ($p < 0.001$).

A possibility is that the variables exhibit unit roots, however because our panel is unbalanced our options for testing are limited. We use Fisher-type tests (Choi 2001). This consists in applying a standard test (Augmented Dickey-Fuller or Phillips-Perron) to each time series, aggregating the p-values, and testing the null hypothesis that all panels contain unit roots, against the alternative that at least one panel is stationary. The Fisher-type tests are based on the $T \to \infty$ asymptotic, with finite or infinite N depending on the statistics. All four statistics derived by Choi (2001) deliver a near zero p-value for both the log of experience and the log of person-hours per unit, so we reject that all series contain a unit root.

Since there is autocorrelation but it is not as strong as to suggest a first-difference model, we follow two separate directions. First, we simply estimate a Fixed Effects model with autocorrelated errors, with two different estimators for the autocorrelation parameter (Durbin Watson or the autocorrelation of residuals, both computed on the

Table 8: Time Series models for *Labor Productivity*

	AR1		Lagged Dep.Var.		
	DW	Corr.	OLS	OLS	Arellano-Bond
Experience	-0.169***	-0.349***	-0.219***	-0.029**	-0.026
	(0.019)	(0.016)	(0.029)	(0.009)	(0.100)
Time	0.004*	0.008***	-0.002*	-0.003***	-0.003
	(0.002)	(0.002)	(0.001)	(0.001)	(0.010)
Personhours(t-1)			0.771***	0.772***	0.744***
			(0.022)	(0.022)	(0.211)
Experience(t-1)			0.159***		
			(0.022)		
Observations	2882	2882	2830	2830	2660
AR(1)	0.83	0.65			
Experience, long-run			-0.260	-0.126	-0.101

within transformed data). These two methods of computing autocorrelations result in noticeably different results, yet in both cases the sign of the exogenous time trend is reversed and the coefficient of experience remains important and strongly significant (first two columns of Table 8).

The second approach is to consider that residual autocorrelation is caused by misspecification, whereby the lagged values of the regressor and/or the regressand are missing. The more complete model

$$\log c_{it} = \kappa_i + a \log c_{i,t-1} + \beta \log Z_{i,t} + \beta_2 \log Z_{i,t-1} + \eta_{it}$$

nests a large class of dynamic linear models (Hendry 1995). The results of estimating this using OLS are in column 3, showing coefficients of opposite signs for experience and its lagged value. Removing the lag of experience (col 4), the autoregressive parameter remains the same, and the estimated long-run effect[10] decreases by half. Finally (col. 5), although we have a fairly "long" panel whereby the Nickell bias is unlikely to be large, we estimate the same equation using the two step Arellano & Bond's (1991) estimator with all possible instruments and robust (Windmeijer) standard errors, and find similar results.

Contracts. We start again with Wooldridge's test for AR(1) residuals and as for the *Labor productivity* data, we strongly reject the null of no autocorrelation. However, in contrast to the *Labor productivity* data, all the unit root tests we performed (Choi 2001, Im et al. 2003, Levin et al. 2002, Hadri 2000, Breitung 2001, Harris & Tzavalis 1999) systematically suggested that both the log of contract prices and the log of production experience have unit roots.

[10]This is estimated as as the sum of the coefficient(s) of experience divided by one minus the autoregressive parameter.

Thus we tested for co-integration, using Pedroni's (1999) test statistics. None of the 7 test statistics suggested rejection of the null of no co-integration. This is not too surprising, as we do not see a compelling reason for the existence of a strong relationship between the *levels* of cost and experience, so that a departure from this long term level relationship would imply an error-correction behavior and a return to this trend[11]. Overall, these tests suggest that costs and experience are related in difference, that is, a change in experience is associated with a change in costs.

D.2 Coefficient heterogeneity

In the main text, we have reported results with either both α and β common across all products, or separate regressions for each product. Here we investigate the results when we constrain only one of the two parameters to be the same across products and allow the other one differ.

Time trend heterogeneity only. We can investigate heterogenous time trends by estimating a fixed effect regression on the first differenced values, that is

$$\Delta \log c_{it} = \kappa_i + \beta \Delta \log Z_{it} + \eta_{it}. \tag{9}$$

The results in Table 9 show results that are robust in the case of the Labor Productivity dataset, but evaporate entirely in the Contracts data. This is not too surprising given what we had reported using individual-level regressions in Figs. 2 and 4 in the main text.

Table 9: Fixed effects on the first differences

	Labor Productivity	Contracts
Experience	-0.210***	0.004
	(0.020)	(0.083)
Observations	2830	301
R^2	0.105	0.000

Experience effect heterogeneity. We can estimate heterogeneous slopes for experience using Swamy's (1970)'s random coefficients model and the Mean Group estimator of Pesaran & Smith (1995). We estimate these two models on the first differenced variables.

The results are in Table 10. The point estimates in the *Labor Productivity* dataset suggest a stronger effect of experience than in our main specification, while the reverse is true in the *Contracts* dataset. In all cases, however, the standard errors are such that the distributions for the coefficients presented here and the coefficients estimated in the main text overlap significantly.

[11]Note also that experience cannot decrease, which would imply additional restrictions on the error-correction model.

Table 10: Heterogenous coefficients models (Swamy and Mean group)

	Labor Productivity		Contracts	
	Swamy	MG	Swamy	MG
Experience	-0.272**	-0.362***	-0.031	-0.035
	(0.087)	(0.082)	(0.061)	(0.047)
Constant	-0.013	-0.015	-0.007*	-0.008*
	(0.016)	(0.015)	(0.004)	(0.003)
Observations	2817	2817	301	301

D.3 Instrumenting by lagged values

Because unit and labor costs are total costs divided by output, output appears on both sides of the equations.

As shown in Reed (2015), using a lagged value of the regressor to deal with simultaneity is not appropriate, but using the lagged values as instruments in an IV regression can be effective, if the lagged regressors are themselves not regressors in the true data generating process, and when the lagged regressors are sufficiently correlated with the (instrumented) regressors.

Table 11 reports instrumental variable estimates for the main specification (first-difference) using the first lag of (log) production as instrument for (log) production, and first lag of (log) experience as instrument for (log) experience. We cannot perform this robustness check for the *USMH* data due its structure.

Table 11: Instrumental variable estimates

	Labor productivity		Contracts	
Experience	-0.209***	-0.219***	-0.123***	-0.124***
	(0.021)	(0.018)	(0.033)	(0.029)
Time	-0.021***	-0.021***	-0.004	-0.004**
	(0.005)	(0.004)	(0.002)	(0.001)
Production	-0.025		-0.007	
	(0.014)		(0.083)	
N	2578	2719	301	301
R^2 within	0.70	0.70	0.76	0.77
R^2 overall	0.00	0.00	0.12	0.13

The results are very similar to those reported in the main text. We also performed these regressions using the fixed effect, rather than first-difference, estimator, again finding results very similar to those reported in the main text.

We have considered other instrumental variable approaches. One approach is to use demand side instruments, for instance battle-related variables, as one may have thought that higher losses of materiel led to an increase in production, and was not correlated with weapons costs decreases. However, as we argued from historical analysis, production operated at maximum capacity, guided by long-term (yearly) targets, and thus was *not* driven by battlefield losses. A second approach would have been to use supply-side instruments, such as the provision of raw materials; because these were in very short supply, they constrained production but their supply may have been argued to be unrelated to cost decreases (but note that there is evidence of induced technical change during the war to save on raw materials). Here we faced the issue that it is virtually impossible to construct product-level instruments.

D.4 Initial experience

Contracts To evaluate the robustness of the results to a different evaluation of the prior experience coefficient, we re-construct experience using values of ζ multiplied by a factor f, with $f = 0 \dots 5$. Fig. 6 reports the results, showing that indeed the results would change noticeably if we misestimated prior experience by an important factor. The third panel, which shows the share of the decrease in cost attributed to the exogenous time trend, shows that if the true ζs were all 20 times lower ($f = 0.05$), the exogenous time trend would explain all cost decrease, and the "learning" parameter would be close to zero. For even smaller values of f, the sign of $\hat{\beta}$ would even change. On the other hand, if we misestimated all the prior experience coefficients by a factor of 2 ($f = 1/2$ or $f = 2$), say, our main conclusion would not be fundamentally affected.

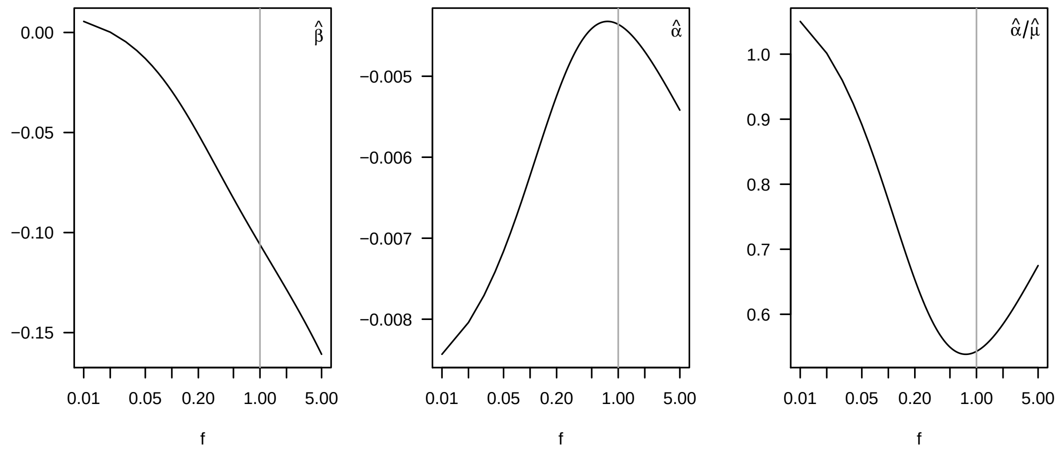

Figure 6: Estimated coefficient of the first difference regression of the log of contract prices on the log of experience and an exogenous time trend, for different values of a factor f that multiplies our baseline vector of estimates of prior experience ζ. The rightmost panel shows $\hat{\alpha}$ divided by the average cost decrease $\hat{\mu} = -0.008$ (as reported in Table 6 in the main text).

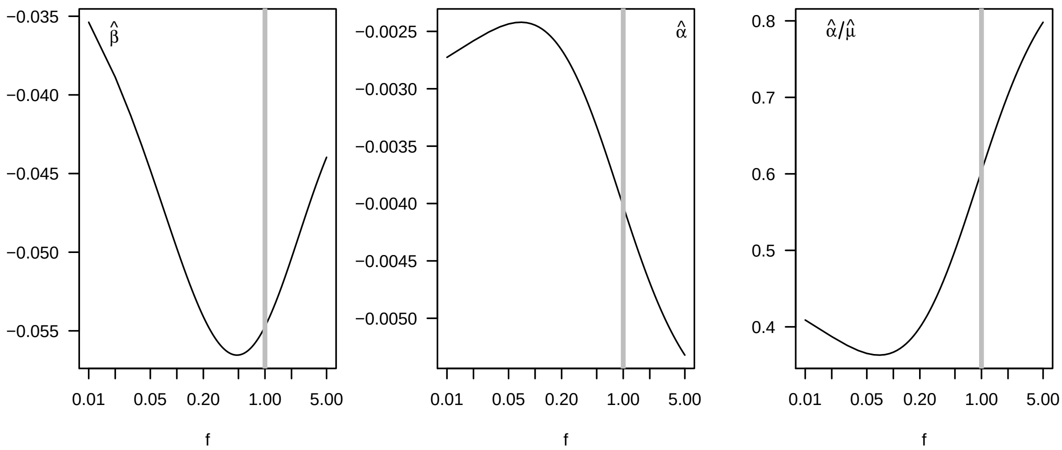

Figure 7: Estimated coefficient of the fixed-effect regression of the log of USMH unit costs on the log of experience and an exogenous time trend, for different values of a factor f that multiplies our baseline vector of estimates of prior experience ζ. The rightmost panel shows $\hat{\alpha}$ divided by the average cost decrease $\hat{\mu} = -0.008$ (as reported in Table 6 in the main text).

OMPUS-USMH. Fig. 7 shows the robustness of the results to a change of the estimates of initial experience by a factor f, as for the *Contracts* data. Again, the results do change sensibly, but overall the results are fairly robust: it would take a very different, implausible change to the estimates of initial experience to alter our conclusion that experience and the exogenous time trend both explain an important share of the cost trend.

Labor Productivity. In the main text, we did not use data corrected for prior experience (see Section B.3 for a discussion). If we apply the corrections suggested by the discussion in Section B.1 for more aggregated categories, we would apply $\zeta = 0.2$ for aircraft, $\zeta = 0.05$ for ships, and, say, $\zeta = 1$ for Ford. In this subsection we apply this correction, and take it as a baseline on which we apply a factor f as above (for $f = 0.01$, the coefficients correspond almost exactly to the coefficients reported in Table 3 in the main text, where $f = 0$). Again we observe some change in the results, but the overall qualitative conclusion remains.

We also note that increasing prior experience tends to worsen the problem of collinearity. The estimated effect of experience on individual time series is less robust to the inclusion of a time trend. In Fig. 2 in the main text, where there is no prior experience correction ($f = 0$, i.e. $\zeta = 0$), the points lie fairly well along the unit line and the correlation between $\hat{\beta}_i(\alpha_i = 0)$ and $\hat{\beta}_i(\alpha_i \neq 0)$ is 0.37. In the baseline correction ($f = 1$), this correlation falls to 0.16.

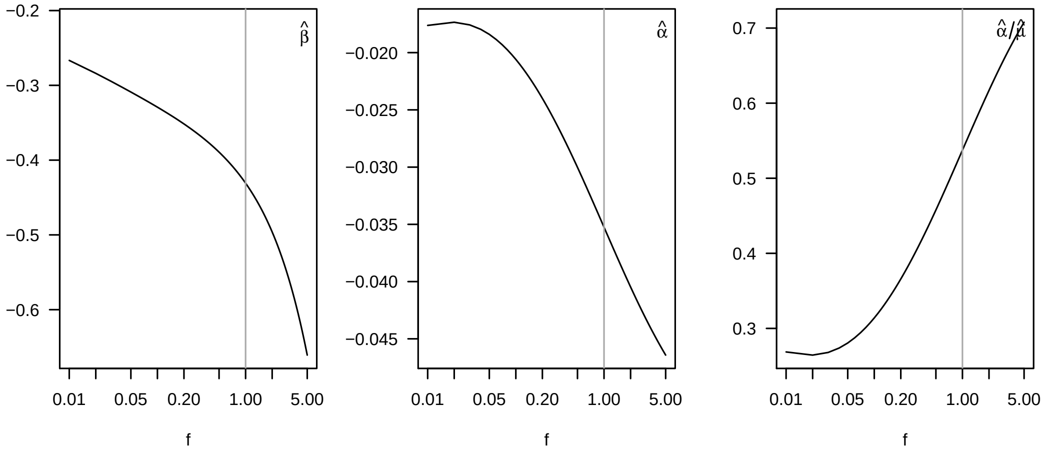

Figure 8: Estimated coefficient of the first difference regression of the log of person-hours on the log of experience and an exogenous time trend, for different values of a factor f that multiplies the vector of estimates of prior experience ζ described in this appendix. The rightmost panel shows $\hat{\alpha}$ divided by the average cost decrease $\hat{\mu} = -0.066$ (as reported in Table 6 in the main text).

The robustness checks described here do not account for the fact that we may have mis-estimated prior experience coefficients much more in some categories than in others. We do not report specific robustness checks for this, but during the process of revising the estimates of the individual ζs, we have re-estimated our main specification several times and while the results somewhat change, as above the main result is not fundamentally affected, with both experience and the exogenous time trend explaining important shares of cost decrease.

All considered, while we acknowledge that correcting for initial experience is difficult, we believe that our method represents a substantial step towards more realistic estimates than simply not correcting, or applying a correction based on constant exponential growth. We believe that our estimates of prior experience are highly unlikely to be systematically wrong by more than a factor of 5, so our key results would not be dramatically affected. That said, there is a lot of heterogeneity among products and our method necessarily produces estimates that could be wildly incorrect for specific products. Our sources, data, and metadata are available, making it possible for historians interested in specific products to build upon and improve our work.

D.5 Comparing the datasets

The *OMPUS-USMH* and *Contracts* datasets contain, in principle, overlapping information. Many detailed products in the *OMPUS-USMH* form part of the basis for the price indices in the *Contracts* datasets. To give estimates of prior experience, in Section B.3, we have built a concordance table between the OMPUS Table of Content (ToC) and the War department services (Table 4). Here we exploit this concordance table to compare the estimated coefficients in Fig. 9. We cannot consider the *OMPUS-USMH* Ships, which cannot be matched with war departments available in *Contracts*, and we omit Transportation, for which only one *OMPUS-USMH* product is available.

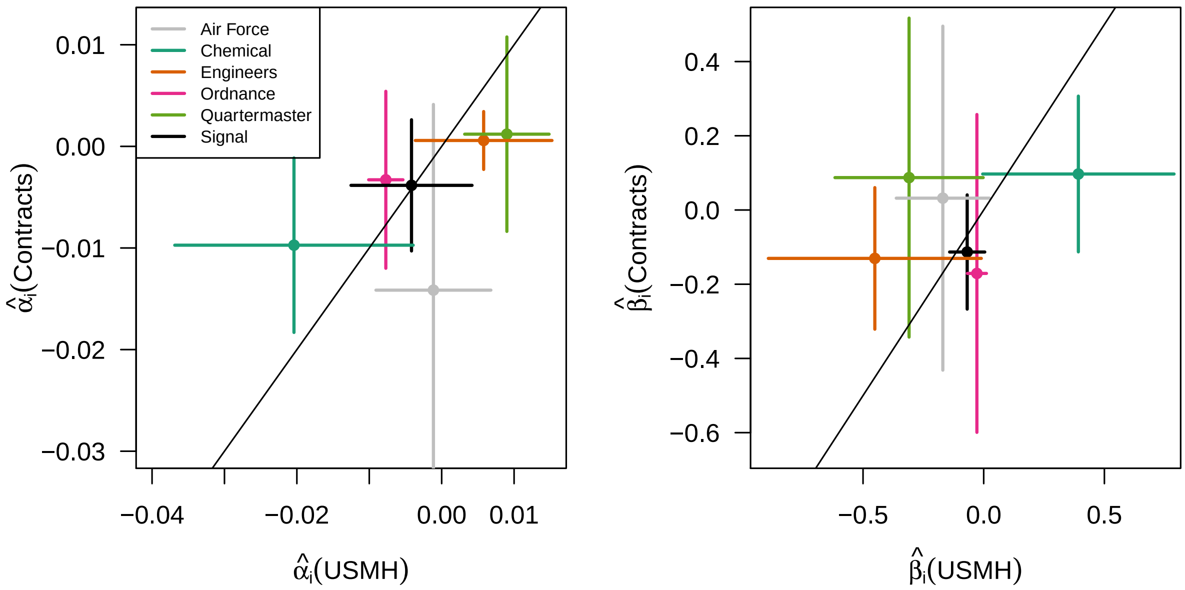

Figure 9: Comparison of the *OMPUS-USMH* and *Contracts* sector-level results.

The estimates of the exogenous technological progress $\hat{\alpha}$ first (left panel) are fairly similar, with a correlation of 0.57. In contrast, the estimates of the effect of experience $\hat{\beta}$ can be quite different, though the correlation remains around 0.33. The estimates for Quartermaster, in particular, are very different. However, the standard errors are very large, and often overlap the identity line, suggesting that the two datasets do not necessarily provide significantly different estimates, and legitimizing our approach of pooling the different war departments.

D.6 Controlling for inflation

During the war, the prices of inputs, including wages, tended to increase, although moderately because of price controls. These input price changes bias our estimates of the effect of experience, which are likely to be higher than what we measure under the assumption of constant input prices.

We cannot control for the price of inputs precisely, due to the lack of available data at a granular level, so we have to resort to an aggregate price index. Of course, even within each dataset the products are quite heterogeneous in terms of their input mix. To control for input prices in this context, we also show a specification which allows each product to have a separate coefficient for the effect of the price index, that is, we interact the price index with the individual dummies (for *OMPUS-USMH*, we used war departments instead of individual products as the basis for interaction terms; for *Labor productivity*, 5 interacted dummies are removed because of perfect multicollinearity).

We used the Producer Price Index for All Commodities (PPIACO), available from FRED. Table 12 reports the results, showing that our main results do not change substantially.

Table 12: Adding PPI as dependent variable

	Labor Productivity		USMH		Contracts	
Experience	-0.219***	-0.222***	-0.061***	-0.043*	-0.110*	-0.104
	(0.022)	(0.022)	(0.017)	(0.018)	(0.042)	(0.054)
Time	-0.024***	-0.023***	0.003	-0.003	-0.005	-0.005
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
PPI	0.899		-3.901*		0.277*	
	(0.593)		(1.752)		(0.095)	
PPI Interacted	No	Indiv.	No	War Dep.	No	Indiv.
N	2830	2830	1046	1046	301	301
R^2	0.126	0.177	0.174	0.224	0.057	0.072

D.7 External learning

A large literature has looked at experience spillovers explicitly, attempting to estimate cross-plant or cross-product spillovers by regressing costs of product i on experience producing i and experience producing j. Here we attempt to capture spillovers at the larger level of the war economy, by constructing an aggregate time series of 'War Effort". A negative effect on cost would indicate spillovers, whereas a positive effect would suggest that aggregate production negatively affects individual products productivity, perhaps due to scarce inputs, which was the case in the war economy. We take the quantity index for the whole War Departments from the *Contract Prices* dataset, that is, the solid black line in Fig. 4. Cumulative War effort is the cumulative, using the estimated prior experience from Table 5.

Table 13: Adding Total War effort as dependent variable

	Labor Productivity		USMH		Contracts	
Experience	-0.214***	-0.211***	-0.063***	-0.066***	-0.106	-0.117*
	(0.022)	(0.022)	(0.017)	(0.017)	(0.043)	(0.044)
Time	-0.023***	-0.022*	-0.003***	0.042***	-0.004	-0.007
	(0.004)	(0.010)	(0.001)	(0.011)	(0.003)	(0.003)
War Effort	0.087**		-0.208***		-0.000	
	(0.032)		(0.051)		(0.008)	
Cumul. War Effort		-0.039		-1.788***		0.129
		(0.376)		(0.412)		(0.066)
N	2810	2810	1046	1046	301	301
R^2	0.123	0.120	0.192	0.191	0.047	0.050

The results are in Table 13. The estimated effects of the "War effort" variables are inconsistent across datasets, and the effects of individual products' experience do not change as compared to our main estimates.

D.8 Depreciation of experience

An important issue in the literature is whether applying a depreciation to experience improves the fit. Usually, one specifies a perpetual inventory method formula for experience and attempts to estimate the depreciation rate. For instance, Levitt et al. (2013) use non-linear least squares.

A specific problem we have here is that assuming depreciation should logically imply that we decrease the estimate of previous experience. Unfortunately, we were able to give estimates of previous experience but not of how it unfolded over time - thus we cannot easily apply a depreciation factor to it.

Here we simply omit this issue, and take the same estimates of initial experience as in the main text[12]. We then cumulate production using a depreciation factor, as

$$Z_t = \delta Z_{t-1} + q_t.$$

Instead of estimating δ, we fit the model for a range of values of $\delta \in (0.8, 1)$ and provide the R^2 of the regression (to show what Nonlinear Least Squares would estimate), the estimated coefficients for time and experience, and the implied share of exogenous progress.

[12] Assuming a lower initial experience, e.g. depreciated initial experience = initial experience /6, does not change the patterns in Fig. 10.

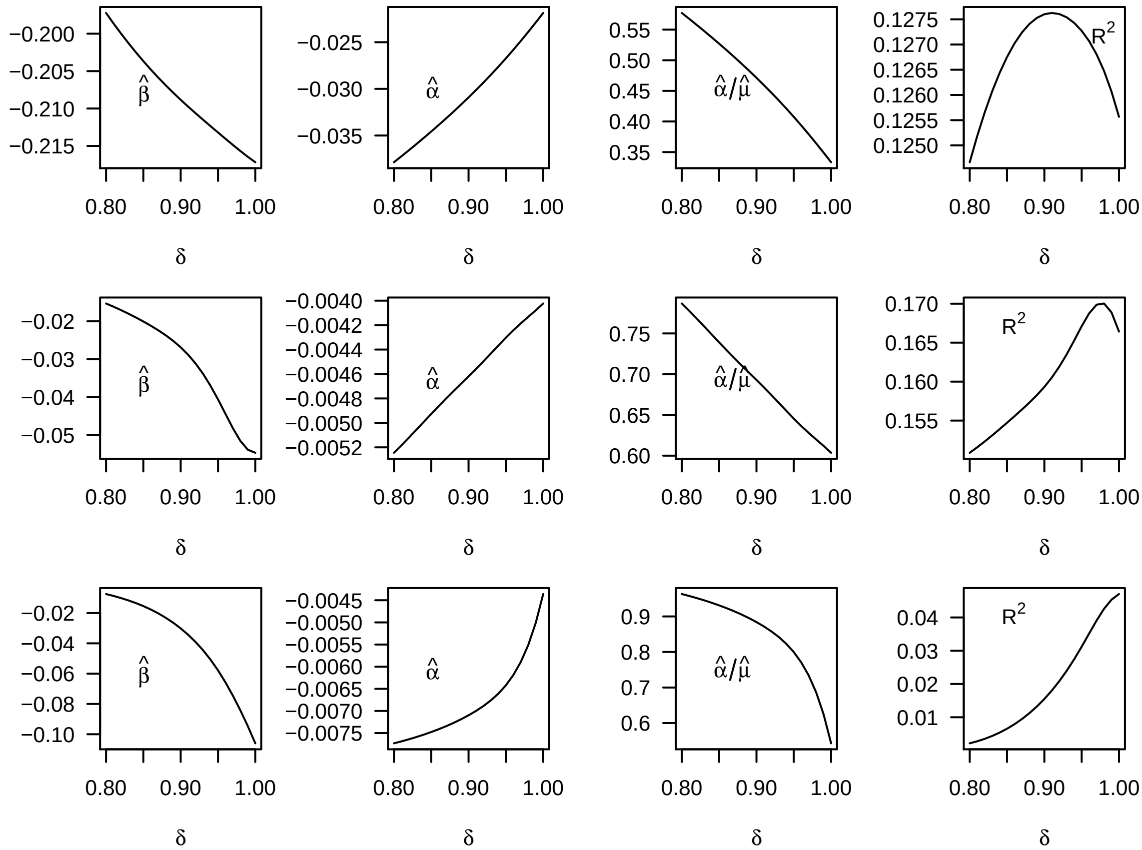

Figure 10: Change of the main result as a function of the depreciation of experience parameter δ. Top: *Labor productivity*; Center: *OMPUS-USMH*; Bottom: *Contracts*

The results are in Fig. 10. The robust pattern that emerges is that allowing $\delta < 1$ would always make $\hat{\beta}$ less negative and $\hat{\alpha}$ more negative, and the estimate of the share of exogenous progress larger. However, the best fit models would imply no or only a moderate increase of the estimated share of exogenous progress. For instance, in the "worst" case, *Labor productivity*, $\hat{\delta} = 0.91$ implies a substantial annual depreciation of $0.91^{12} = 0.32$, but the share of exogenous progress rises only from 0.33 to 0.46.

D.9 Overlap between estimated coefficients

Our main estimates for the parameters α and β in the three datasets, summarized in Table 6 in the main text, are quite different. This is not surprising since the estimated value of β in each dataset is itself a pooled estimate for somewhat heterogenous β_is at the individual levels (Figs 2 and 4 in the main text). For instance, our estimate of β in the *Labor Productivity* dataset is 4 times higher than in the *OMPUS-USMH* data. Rather than providing formal significance testing, we want to make a broader point: while the estimated coefficients may be different from one dataset to the other, the fact that both exogenous and endogenous progress account for relatively similar shares of progress is relatively robust.

We assume that the distribution of these estimates is normal, with a mean as the point estimate and a standard deviation as the standard error (this is a conservative assumption, compared to assuming a t-distribution, which would be more widespread and produce higher overlaps). For instance, looking at column 5 of Table 2 in the main text, we assume that the true coefficient β for the *Labor Productivity* dataset follows $\beta \sim \mathcal{N}(0.217, 0.022^2)$.

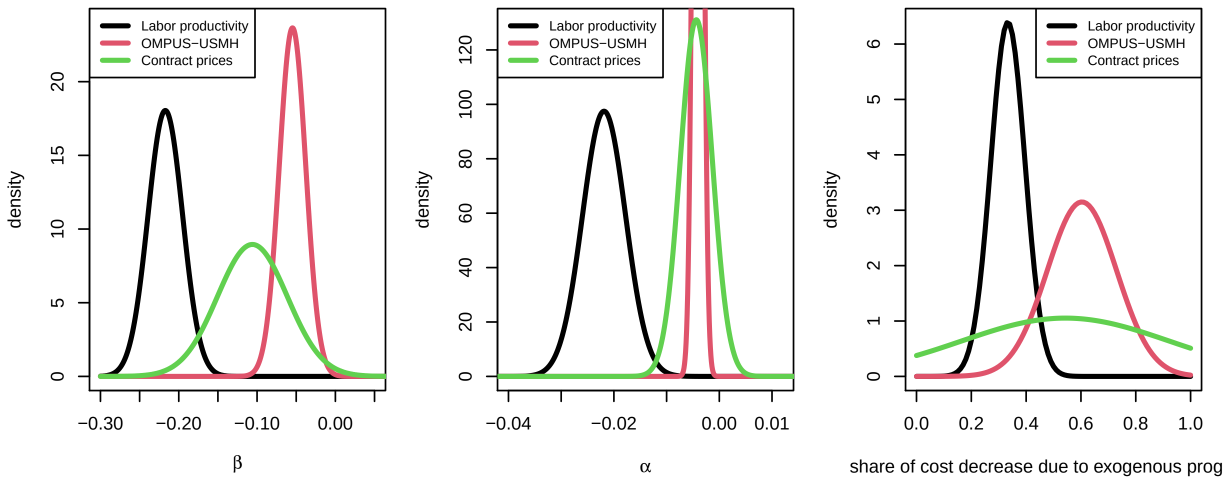

Figure 11: Distribution of the estimated coefficients, using the key results as selected for the Discussion section in the main text.

Fig. 11 shows the results. Overall, the *OMPUS* and the *Contract prices* datasets tend to have a good overlap for both β and α, while the *Labor Productivity* dataset has stronger (more negative) estimates. This is because, in the *Labor Productivity* dataset, there is more cost decrease to explain: costs declines have been much stronger in airplanes than in other categories, and this dataset is dominated by this category of products. This is why we believe that a more reasonable quantity to look at is relative: the share of cost growth rate $\hat{\mu}$ that is accounted for by exogenous vs endogenous progress.

Unfortunately, the distribution of the ratio $\hat{\alpha}/\hat{\mu}$ is difficult to derive. If $\hat{\alpha}$ and $\hat{\mu}$ were independent and both normally distributed, the distribution would be Cauchy, but here $\hat{\alpha}$ and $\hat{\mu}$ are dependent since they are computed from the same data. While approximate formulas have been developed for the variance of the distribution of ratios of correlated normally distributed random variables, these formulas are approximate, include population (rather than sample) moments, and require an estimate of the covariance between the variables. A key point to note is that while $\hat{\alpha}$ may have a fairly high variance, due to the multicolinarity issues we have highlighted throughout the paper, $\hat{\mu}$ is a simple sample average, and our datasets are fairly large, so it is likely to have a fairly small variance.

As a result, we propose to circumvent this issue with the following thought experiment. We take $\hat{\mu}$ as a given scalar (i.e. non stochastic), and we ask how the ratio $\hat{\alpha}/\hat{\mu}$ is distributed, considering $\hat{\mu}$ as fixed but $\hat{\alpha}$ as distributed according its estimated distribution from our main regressions. In other words, we ask: taking the mean cost growth rate of each dataset as given, and taking a reasonable proxy for uncertainty on the rate of exogenous progress measured in each dataset, is it plausible that the contribution of exogenous progress is similar across datasets?

More precisely, we assume that $\alpha \sim \mathcal{N}(\hat{\alpha}, \sigma_\alpha^2)$ and $\mu = \hat{\mu}$, so that share exo $\equiv \frac{\alpha}{\mu} \sim \mathcal{N}\left(\frac{\hat{\alpha}}{\hat{\mu}}, \left(\frac{\sigma_\alpha}{\hat{\mu}}\right)^2\right)$, where $\hat{\mu}$ is the average growth rate of cost, as reported in column 1 of Table 6 in the main text. The procedure should be slightly amended for the *OMPUS* data, where the share of exogenous progress is computed from Eq. 7, that is $E[\text{share exo}] = \frac{\frac{1}{n}\sum_i \tau_i}{\frac{1}{n}\sum_i \Delta^{\tau_i} \log c_i} E[\alpha]$, so we use $\text{Var}[\text{share exo}] = \left(\frac{\frac{1}{n}\sum_i \tau_i}{\frac{1}{n}\sum_i \Delta^{\tau_i} \log c_i}\right)^2 \text{Var}[\alpha]$.

The overlap between the three distributions is now more evident. Overall, this suggests that while concluding about specific values for elasticities is delicate, the idea that changes in costs will in general be due to both exogenous and endogenous forces in "relatively similar proportions" is supported by the data.

D.10 Assuming known economies of scale

Recall our main regression

$$\Delta \log c_{it} = -\frac{a}{s} - \frac{b}{s}\Delta \log Z_{it} + \left(\frac{1}{s} - 1\right)\Delta \log Q_{it}$$

This can be rewritten as

$$s\Delta \log c_{it} - (1-s)\Delta \log Q_{it} = -a - b\Delta \log Z_{it}$$

In other words, if we know the economies of scale parameter s, we can compute the LHS and regress it on an intercept and the growth of experience to identify the parameters of interest, a and b, directly.

Our goal is to separate overall *contributions* of exogenous and endogenous effects, so ultimately we want to see how $-\frac{\hat{a}}{s}$ changes for different assumed values of s.

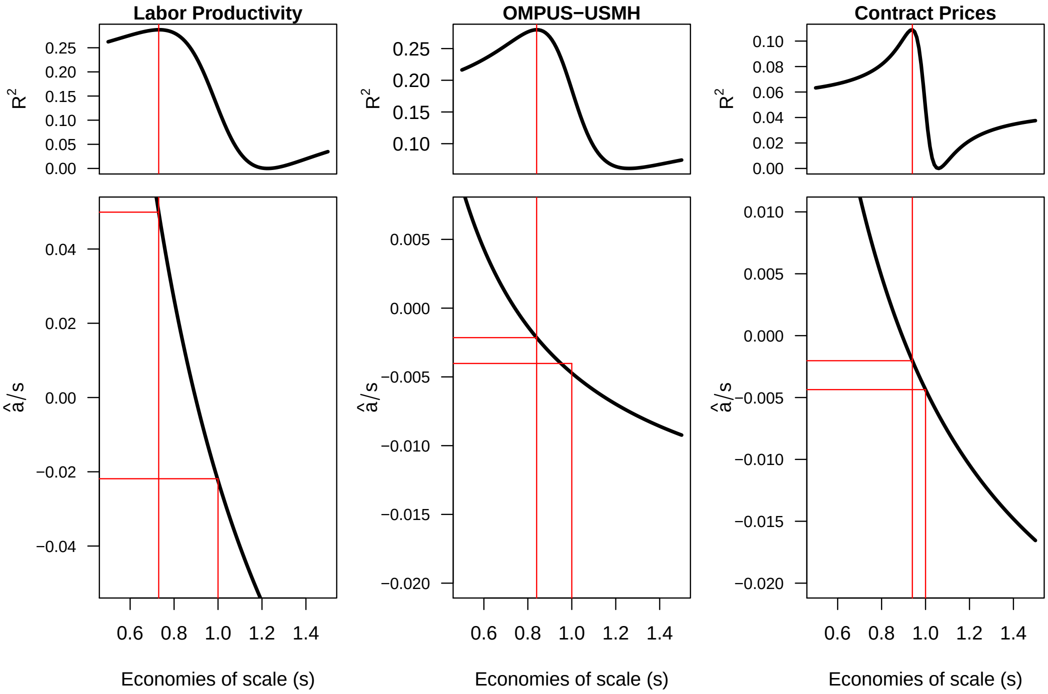

Figure 12: Value of estimated effect of experience $\hat{\beta}$ as a function of the assumed value of the economies of scale parameter s. The blue lines indicate the values of $\hat{\beta}$ when $s = 1$. These corresponds to the values reported in Tables 3, 4 and 5 in the main text, except for OMPUS-USMH because here we need to remove all the observations with Q=0, whereas we do not need to do this when the observations of Q are not needed to perform a transformation of variables. The red lines indicate the pairs $(s, \hat{\beta})$ that correspond to the highest R^2 value.

Figure 12 shows the results. Assuming non constant returns to scale could, indeed, change the estimated value of the intercept quite substantially, depending on what we consider to be "reasonable" departures from the assumption of constant returns. We also plot the goodness of fit of these estimate, as an indication of what might be a reasonable value. In all cases, the suggested value of s would be lower than one, and this would always correspond to a weaker overall contribution of exogenous technological progress.

References

Arellano, M. & Bond, S. (1991), 'Some tests of specification for panel data: Monte carlo evidence and an application to employment equations', *The Review of Economic Studies* **58**(2), 277–297.

Army Air Forces (1947), *The source book of World War II basic data. Airframe industry, Vol. I, direct man-hours - progress curves*.

Ayres, L. P. (1919), *The War with Germany: A Statistical Summary*, Government Printing Office.

Breitung, J. (2001), The local power of some unit root tests for panel data, *in* 'Nonstationary panels, panel cointegration, and dynamic panels', Emerald Group Publishing Limited, pp. 161–177.

Broadberry, S. & Harrison, M., eds (2005), *The Economics of World War I*, Cambridge University Press.

Cain, L. P. (2006), *Historical Statistics of the United States, Millennial Edition*, chapter Domestic sales, imports, and exports of passenger cars and trucks: 1931-1996.

Carter, S. B., Garntner, S. S., Haines, M. R., Olmstead, A. L., Sutch, R., Wright, G., Atack, J. & Bateman, F. (2006), *Historical Statistics of the United States Millennial Edition Online, Table Dd366-436: Physical output of selected manufactured products: 1860-1997*, Cambridge University Press.

Casella, G. & Berger, R. L. (2001), *Statistical inference, 2nd ed.*, Cengage Learning.

Choi, I. (2001), 'Unit root tests for panel data', *Journal of International Money and Finance* **20**(2), 249–272.

Coates Jr, J. B. (1959), 'The history of the US army medical department in World War II', *Bulletin of the Medical Library Association* **47**(3), 264.

Coker, K. R. & Stokes, C. E. (1991), *A Concise History of the U.S. Army Signal Corps*, Army Signal Center and Fort Gordon GA.

Connors, J. (2010), *Engines of Pratt and Whitney - A Technical History*, American Institute of Aeronautics and Astronautics.

Crawford, R. H. & Cook, Lindsey, F. (1952), *US Army in World Wart II: Statistics - procurement*.
URL: http://www.alternatewars.com/BBOW/Stats/USA_in_WW2_Stats-Procure_9-APR-52.PDF

Evans, P. (1982), 'The effects of general price controls in the united states during world war ii', *Journal of Political Economy* pp. 944–966.

George, J. L. (n.d.), *History of Warships from Ancient Times to the Twenty-First Century*, Naval Institute Press.

Hadri, K. (2000), 'Testing for stationarity in heterogeneous panel data', *The Econometrics Journal* **3**(2), 148–161.

Harris, R. D. & Tzavalis, E. (1999), 'Inference for unit roots in dynamic panels where the time dimension is fixed', *Journal of Econometrics* **91**(2), 201–226.

Hecks, K. (1990), *Bombing 1939 - 1945: The Air Offensive Against Land Targets in World War II*, Edmundsbury Press.

Hendry, D. F. (1995), *Dynamic econometrics*, Oxford University Press on Demand.

Herman, A. (2012), *Freedom's Forge: How American Business Produced Victory in World War II*, Random House.

Hyde, C. K. (2013), *Arsenal of Democracy: The American Automobile Industry in World War II*, Wayne State University Press.

Im, K. S., Pesaran, M. H. & Shin, Y. (2003), 'Testing for unit roots in heterogeneous panels', *Journal of Econometrics* **115**(1), 53–74.

Killblane, R. (2012), '70 years of the transportation corps', *Professional bulletin of the the United States army sustainement* **44**(4).
URL: https://alu.army.mil/alog/issues/julaug12/70_Years_transportation_Corps.html

LeMay, C. E. & Yenne, B. (1988), *Superfortress: The Story of the B-29 and American Air*

Power, McGraw-Hill Companies.

Levin, A., Lin, C.-F. & Chu, C.-S. J. (2002), 'Unit root tests in panel data: asymptotic and finite-sample properties', *Journal of Econometrics* **108**(1), 1–24.

Levitt, S. D., List, J. A. & Syverson, C. (2013), 'Toward an understanding of learning by doing: Evidence from an automobile assembly plant', *Journal of political Economy* **121**(4), 643–681.

Lorell, M. A. (2003), The u.s. combat aircraft industry, 1909-2000: Structure, competition, innovation, Technical report, RAND Corporation.

Mauroni, A. (2015), 'The U.S. army chemical corps: Past, present and future'.
URL: https://armyhistory.org/the-u-s-army-chemical-corps-past-present-and-future

Mishina, K. (1999), Learning by new experiences: Revisiting the flying fortress learning curve, *in* 'Learning by doing in markets, firms, and countries', University of Chicago Press, pp. 145–184.

Pattillo, D. M. (1998), *A history in the making: 80 turbulent years in the American general aviation industry*, McGraw Hill Professional.

Pedroni, P. (1999), 'Critical values for cointegration tests in heterogeneous panels with multiple regressors', *Oxford Bulletin of Economics and Statistics* **61**(S1), 653–670.

Pesaran, M. H. & Smith, R. (1995), 'Estimating long-run relationships from dynamic heterogeneous panels', *Journal of Econometrics* **68**(1), 79–113.

Reed, W. R. (2015), 'On the practice of lagging variables to avoid simultaneity', *Oxford Bulletin of Economics and Statistics* **77**(6), 897–905.

Risch, E. (2014), *The Quartermaster Corps: Organization, Supply and Services, 2 vol.*, Washington DC: Center for Military History.

Ross, S. H. (2003), *Strategic Bombing by The United States in World War II: The Myths and the Facts*, McFarland & Company.

Rostker, B. (2013), *Providing for the Casualties of War: The American Experience Through World War II*, RAND Corporation.

Rubis, K. (2012), 'The history of ordnance in america', *Professional bulletin of the United States army sustainment* .
URL: https://alu.army.mil/alog/issues/MayJune12/history_ordance.html

Swamy, P. A. (1970), 'Efficient inference in a random coefficient regression model', *Econometrica* pp. 311–323.

Thompson, P. (2001), 'How much did the liberty shipbuilders learn? new evidence for an old case study', *Journal of Political Economy* **109**(1), 103–137.

Thompson, P. (2007), 'How much did the liberty shipbuilders forget?', *Management Science* **53**(6), 908–918.

Thompson, P. (2012), 'The relationship between unit cost and cumulative quantity and the evidence for organizational learning-by-doing', *Journal of Economic Perspectives* **26**(3), 203–224.

Thornton, R. A. & Thompson, P. (2001), 'Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding', *American Economic Review* **91**(5), 1350–1368.

U.S. Bureau of Economic Analysis (2017), Personal consumption expenditures excluding food and energy (chain-type price index), Technical report. [DPCCRG3A086NBEA], retrieved from FRED, Federal Reserve Bank of St. Louis;

https://fred.stlouisfed.org/series/DPCCRG3A086NBEA.
War Production Board (1945), *Wartime Production Achievements and the Reconversion Outlook*.
White, G. (1995), *Allied Aircraft Piston Engines of World War II*, Graham White.
Wooldridge, J. M. (2002), *Econometric analysis of cross section and panel data*, MIT Press.