Demand Shocks, Procurement Policies, and the Nature of Medical Innovation: Evidence from Wartime Prosthetic Device Patents

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August 2, 2023

Abstract:

We show that the demand shocks associated with the U.S. Civil War and World War I led to substantial increases in prosthetic device patenting (relative to patenting in other medical and mechanical technology classes). Through analyses of patent texts, we find that the Civil War led inventors to focus on production process improvements, while World War I did not. Further, we find that inventors emphasized dimensions of product quality that aligned with differences in buyers' preferences across wars. Alongside evidence from the historical record, these findings imply that procurement environments can significantly shape the scientific problems with which inventors engage.

JEL Codes: H57, Procurement; I1, Health; O31, Innovation and Invention

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From 1960 to 2019, U.S. health spending rose from 5 to nearly 18 percent of GDP. Research has documented that the advance of medical innovation underlies a substantial share of this cost growth (Smith, Newhouse, and Freeland, 2009; Cutler, 2004), which raises a variety of questions. First, what factors drive the volume of medical innovation? Second, what leads inventors to focus on reducing costs (e.g., by streamlining production processes) versus improving quality? More generally, what factors shape the specific problems with which medical innovators choose to engage?

Wars and pandemics, among other events, can create acute needs for medical innovation. The COVID-19 pandemic, for example, generated demand for new vaccines, new diagnostic tests, testing infrastructure, and personal protective equipment. The value of new vaccines is widely recognized. Improvements in medical equipment, reductions in production costs, and expansions in productive capacity can also have substantial value when demand rises sharply. This motivates us to study how demand shocks and procurement environments shape the volume of medical innovation, its emphasis on the production process, and its emphasis on dimensions of product quality.

We analyze the effects of demand shocks and procurement environments on the quantity of medical innovation and the product and production process attributes it emphasizes. Our empirical analysis considers two important periods in the history of prosthetic device innovation: the U.S. Civil War and World War I. We begin by presenting key details of these historical contexts, including differences in demand, differences in procurement incentives, and differences in the stated goals of the public procurers. We show that both the Civil War and World War I led to substantial increases in prosthetic device patenting. A point of contrast is that the Civil War led to a much greater focus on cost-conscious innovation while World War I did not. To the best of our knowledge, this analysis provides the first evidence that cost-conscious procurement environments can indeed steer medical innovation in a cost-conscious direction.

Empirically assessing how incentives shape the emphases of inventors requires overcoming two primary challenges. First, existing data sources that categorize patents or clinical trials do not provide information on an invention's detailed economic attributes. Extracting this information requires going deeper into an invention's details. Second, linking procurement environments to the specific attributes on which inventors focus requires analyzing settings across which those environments exhibit variation.

To gain insight into how inventors advanced the frontier of prosthetic device technology, we use machine learning tools to construct a novel data set. We begin by closely reading 1,200 patents from the periods surrounding the U.S. Civil War and World War I. Our selection comprises prosthetic device patents and patents from other medical and mechanical technology classes. Based on these close readings, we code variables describing the economic traits emphasized in each patent. These variables include three traits that we interpret as production-process attributes, three traits that capture distinctive dimensions of product quality, and two additional traits that are less clearly defined as quality or production process traits. We then use machine learning tools to extend our data set to include a much larger set of patents.

The U.S. Civil War and World War I generated dramatic increases in demand for artificial limbs, as amputations were remarkably common. The associated public procurement environments created incentives that differed across the two wars. Our empirical analysis of these episodes includes a combination of time series and difference-in-differences methods. In the time series analysis, we directly examine changes in prosthetic device patents. In the difference-in-differences analyses, we use patents from other medical and mechanical technology classes to construct control groups.

Our first result quantifies the effects of the Civil War and World War I on the quantity of prosthetic device innovation. For several years during these historical episodes, prosthetic device patenting rose by nearly 100 log points relative to patenting in our control groups. Despite analyzing only two events, the relative increases in prosthetic device patenting are strongly statistically distinguishable from zero. Our evidence from patents filed with the U.S. Patent and Trademark Office (USPTO) is supplemented by patents from the short-lived Confederate patent office, as well as from the British and Spanish patent authorities.[1]

For the Civil War period, we have sufficient information to infer an elasticity of innovation with respect to potential revenues. We estimate an elasticity on the order of one for both patenting and firm entry; this is higher than typical estimates of long-run elasticities of medical innovation with respect to long-run changes in market size (Dubois, De Mouzon, Scott-Morton, and Seabright, 2015). Innovation may respond more rapidly to crisis-driven shocks than to standard changes in market size, as Agarwal and Gaule (2022) have observed in the context of the COVID-19 pandemic.

Second, we find that the demand shock associated with the Civil War generated substantial effort to reduce the cost of producing prosthetic devices. During the Civil War, the average prevalence of production process traits doubled in prosthetic device patents but was essentially flat within other technology classes. There was a far more modest shift towards production process traits during World War I. The Civil War era shift towards cost-oriented innovation is consistent with an important role for procurement incentives. As discussed in section 1, the U.S. government's Civil War era procurement program involved modest, fixed-price payments to artificial limb manufacturers, which can create strong incentives for innovation to reduce production costs.[2] As fur-

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[1] In the British patent data, we see a large increase in prosthetic device patenting during World War I and no increase during the U.S. Civil War. Spain participated in neither conflict and the Spanish data exhibit no increase in prosthetic device patenting.

[2] With fixed prices set moderately below baseline costs, for example, sales are not

ther suggestive evidence for the role of procurement incentives, we show that patents for artificial arms, for which profit margins were lower than for artificial legs, exhibit a more substantial shift in emphasis towards cost reduction during the Civil War.

Third, the prosthetic device patents of the Civil War and World War I diverged with respect to dimensions of quality. Civil War-era prosthetic device patents exhibit a substantial increase in emphasis on comfort. By contrast, World War I-era prosthetic device patents de-emphasize comfort and place greater emphasis on occupation-oriented "appliances." That is, inventors increased their emphasis on the development of interchangeable attachments suited for tasks like welding and woodworking. The latter shift connects quite directly to the historical narrative, which highlights an emphasis of governments and medical professionals on the re-employment of veterans with amputated limbs. Civil War and World War I-era differences in emphasis on comfort are plausibly linked to a World War I-era shift in choice away from veterans and toward medical professionals. As detailed below, the historical narrative provides validation for the channels through which the Civil War and World War I-era procurement environments may have altered these dimensions of inventor effort.

Our analysis adds to a broad line of research on the effects of potential profits on innovation. This includes labor economics applications (Acemoglu, 1998; Hémous and Olsen, 2022) as well as a substantial environmental economics literature summarized by Popp (2010, 2019). In the context of health care, research on the effects of potential profits on innovation has focused primarily on pharmaceutical innovation (Finkelstein,

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profitable until manufacturers find ways to reduce production costs. More generally, even when the fixed price exceeds cost, a lower baseline profit per unit increases the returns to innovating to reduce cost relative to the returns to innovating to increase market share by increasing quality.

2004; Acemoglu and Linn, 2004; Budish, Roin, and Williams, 2015).[3] Exceptions include analyses of medical equipment and device patenting by Clemens (2013) and by Galasso and Luo (2017, 2022).[4] We contribute to this literature by providing novel evidence on the effects of large demand shocks on prosthetic device innovation. We additionally provide evidence t hat innovation may respond more aggressively to crisis-driven shocks than one would infer on the basis of long-run elasticity estimates.

We also contribute to the literature on medical innovation by analyzing patent texts to gain insight into innovators' emphases on cost versus dimensions of product quality. Analyses of patent texts have become increasingly common in the innovation literature.[5] We apply text analysis methods to develop the novel data required to make progress in understanding whether procurement environments can shape the particular dimensions of the technical frontier on which inventors focus. Methodologically, we develop several

[3]Additional papers include Blume-Kohout and Sood (2013), who find that research on drugs with high Medicare market shares rose following the introduction of Medicare Part D, Yin (2008), who finds positive effects of the Orphan Drug Act, Dubois, De Mouzon, Scott-Morton, and Seabright (2015), who find that potential profits affect the number of new molecular entities that come to market, and Agarwal and Gaule (2022) who study medical innovation in the context of the COVID-19 pandemic.

[4]Clemens (2013) studies medical equipment patenting surrounding the introduction of Medicare. Galasso and Luo (2017) study the effects of tort reform on medical equipment and device innovation, while Galasso and Luo (2022) study the effects of liability risks faced by the suppliers of medical implants.

[5]See, for example, Khoury and Bekkerman (2016); Bergeaud, Potiron, and Raimbault (2017); Iaria, Schwarz, and Waldinger (2018); Watzinger and Schnitzer (2019); Arts, Cassiman, and Gomez (2018); Cockburn, Henderson, and Stern (2018).

practical insights into best practice methods for this class of machine learning applications. The substance of our findings provides evidence that cost-conscious procurement environments can indeed steer medical innovation in a cost-conscious direction.

The paper proceeds as follows. Section 1 provides historical background and section 2 summarizes the hypotheses that are motivated by our historical settings. Section 3 discusses our novel data set and section 4 our empirical strategy. Section 5 presents our results and section 6 concludes.

1 Civil War and World War I Demand for Artificial Limbs

The U.S. Civil War and World War I were both associated with dramatic increases in demand for prosthetic devices. In this section, we begin by describing the size of these demand shocks. We then provide background on the relevant systems for rehabilitating veterans and procuring artificial limbs.

1.1 The Magnitude of Wartime Demand Shocks

The U.S. Civil War was contested between the armies of the Union and the Confederacy from April 1861 to May 1865. An estimated 35,000 veterans with amputated limbs survived the war on the Union side alone (Linker, 2011, p. 98). Because the government had not formed a permanent bureaucracy for addressing veteran health care needs prior to the war, both the Union and Confederacy implemented ad hoc artificial limb procurement systems as the scope of need became clear. Wartime production levels (Barnes and Stanton, 1866; Hasegawa, 2012) far exceeded pre-war production as documented in the 1860 Census of Manufacturing. In developing our evidence of the effects of Civil War-era demand on innovation, we draw primarily on patents filed with the USPTO, but also consider patents filed with the short-lived Confederate patent office. We look further to

British and Spanish patent counts to provide evidence on patenting in countries that did not participate directly in the Civil War.

World War I produced an estimated 300,000 veterans with amputated limbs worldwide. Relative to the Civil War, demand associated with 4,000 U.S. veterans was relatively modest. Because production capacity was low among the European powers and high in the United States, the U.S.-based artificial limb industry played an important role in satisfying global demand. Great Britain, for example, which was home to an estimated 41,000 surviving veterans with amputated limbs (Guyatt, 2001, p. 98), invited the largest American prosthetic companies "to set up workshops at the main amputee center" (Linker, 2011, p. 99). In developing our evidence of the effects of World War I-era demand on innovation, we study patents from both the United States and Great Britain. In the World War I context, we look to Spanish patent counts to provide evidence on patenting in a non-combatant nation.

1.2 Background on Civil War and WWI-Era Procurement

During the Civil War, the manufacturers of artificial limbs faced a competitive environment in which they were reimbursed on a "fixed-price" basis. To become eligible for purchase through the Union's limb allowance program, artificial limb models had to be certified by a board of physicians.[6] If the board deemed a prototype to be "serviceable," its manufacturer entered the list of manufacturers from which soldiers could select the provider of their artificial limb. Fixed-price reimbursements were set at modest levels relative to manufacturers' stated costs from the pre-war period, and balance billing was

[6]As Hasegawa (2012) documents, General William Hammond convened a panel of physicians to, in Hammond's words, "determine what kind of Artificial Limbs should be adopted for the use of mutilated soldiers."

prohibited (Hasegawa, 2012, p. 37-38).[7]

By World War I, the U.S. had substantively formalized the treatment of veterans with amputated limbs. This occurred within a broader effort to formalize veterans' health care. In addition to being formalized, care for veterans with amputated limbs was mostly centralized at large facilities, including the recently built Walter Reed Hospital.

Progressive Era policymakers worried that veterans with amputated limbs would, like many of their Civil War predecessors, fail to return to gainful employment. A perception of limbless Civil War veterans "pocketing" their allowances and opting out of the labor force impacted World War I-era views regarding care and rehabilitation (Linker, 2011). As Linker (2011, p. 13) writes, "The veterans of America's First World War were expected to become citizen-workers once their military service was over; they were to make useful lives, not to languish at the expense of the US Treasury."

Between the Civil War and World War I, discretion in the choice of artificial limb shifted from veteran to government. During World War I, veterans underwent extensive rehabilitation prior to their return to civilian life, including obligatory use of standard-issue prosthetic limbs. Linker (2011, p. 101) writes that "the OSG [Office of the Surgeon General] forcefully mandated artificial limb wear, creating legislation that made it virtually impossible for US amputee soldiers to be discharged from military service without

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[7]During the latter half of the war, the price for artificial legs was set at $75 (roughly $1,500 in 2018 dollars) and the price for artificial arms was set at $50. A small number of products were authorized for sale at higher rates (Hasegawa, 2012, p. 40). In such cases, the veteran was responsible for the difference between the approved price and the government's allowance of $75 per leg or $50 per arm. These products were meant to be sold at the approved prices on a fixed rate basis with no balance billing. Hasegawa (2012) documents that a leading manufacturer told the government his costs were $150 per artificial leg.

months of rehabilitation and daily routine artificial limb wear." In contrast with the Civil War, demand for artificial limbs was thus shaped to a significant degree by the veterans' medical bureaucracy and to a lesser degree by wounded veterans.

The incentives facing artificial limb manufacturers were shaped by the preferences of World War I-era medical bureaucracies in both the U.S. and Europe. While we cannot know the precise criteria each bureaucracy used in their procurement of artificial limbs, the historical record provides clues regarding approaches to rehabilitation. Medical professionals of the World War I-era de-emphasized comfort in favor of a strict rehabilitation program. Linker (2011, p. 109-114) writes, for example:

> Once surgical healing had been attained... the 'toughening' of the stump by 'pounding it on a firm surface' should be 'vigorously pursued'... Following stump pounding exercises, 'patients usually complained of discomfort'... Another report stated that when amputees were forced to wear artificial limbs soon after surgery, they often 'expressed gratitude when the artificial limb [was] removed.'

In addition to driving a relatively severe program of physical rehabilitation, the desire for social reintegration spurred an emphasis on re-employment. The British government had similar views on the importance of rehabilitation and re-employment.[8] The historical record thus suggests that World War I-era procurers placed substantial emphasis on artificial limbs' capacity to restore an individual's employability.

[8]See, for example, the discussions of British World War I-era rehabilitation and artificial limb manufacturing in Novotny (2017) and Guyatt (2001).

2 Implications of Wartime Demand Shocks for Innovation

We draw on the historical narrative regarding Civil War and World War I-era demand shocks and procurement environments to develop hypotheses regarding the potential effects of these events on prosthetic device innovation. The hypotheses motivated by the historical record are as follows:

First, the large demand shocks associated with both the Civil War and World War I increased incentives for developing novel prosthetic devices. The hypothesis that these demand shocks would increase flows of innovation is perhaps the most standard hypothesis in the literature on demand-driven innovation.

Second, Civil War-era procurement featured low, fixed-price reimbursements. We hypothesize that this regime may have generated an increase in inventor emphasis on cost-conscious innovation. This hypothesis is linked in part to the fact that production costs must be driven below the reimbursement level before sales become profitable.

Third, we hypothesize that the emphasis of World War I-era procurers on veterans' re-employment may have increased inventor emphasis on the capacity for artificial limbs to enhance their wearer's social reintegration and employability. Social reintegration could be facilitated by limbs that more faithfully mimicked the appearance of a natural limb. Employability could be facilitated by a line of artificial limb technology we call "appliances." In this context, the word "appliances" refers to interchangeable artificial limb attachments which serve functions that connect directly to occupational tasks.

Fourth, we hypothesize that the Civil War-era procurement environment may have increased inventors' emphasis on characteristics demanded by veterans, who could choose across products, while the more centralized World War I-era procurement environment prioritized the preferences of the veterans' medical bureaucracy. This final hypothesis has less precise empirical content than hypotheses one through three. It may be relevant to such traits as an artificial limb's comfort and appearance.

3 Patent Data and Text Analysis Methods

We begin this section with a discussion of the historical patent data we use to estimate the effects of wartime demand shocks on overall patent flows. We then discuss the new data we generated through text analysis (or natural language processing) using a combination of close readings and machine learning techniques.

3.1 Historical Patent Data

The first question we attempt to answer is if wartime increases in demand for prosthetic devices increased the rate of prosthetic device patenting. This analysis requires information on 19th and early 20th century patents by technology class. Until relatively recently, the patent data sets analyzed by economists did not facilitate this type of historical analysis. The groundbreaking NBER patent database (Hall, Jaffe, and Trajtenberg, 2001), for example, begins with patents granted in 1963. Economists have recently developed databases extending to the earliest surviving records of the U.S. Patent and Trademark Office (USPTO). To identify historical patents based on their technology classes, we use the database assembled by Berkes (2018).[9] We supplement these data with additional data on Confederate patents, British patents, and Spanish patents.[10]

One shortcoming of the Civil War era patent data is that, before 1873, patents re-

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[9]In a comparison of efforts to compile data on the universe of U.S. patents, Andrews (2019) concludes that the database in Berkes (2018) is "currently the gold standard." Recent work by Berkes and Nencka (2019) and Berkes, Gaetani, and Mestieri (2019) have also been made possible by these data.

[10]Sáiz (2000) and Sáiz, Llorens, Blázquez, and Cayón (2008) generously provided Spanish patent data.

ported the date the patent was issued, but not the date it was filed (Berkes, 2018). Consequently, we organize patents according to their date of issuance throughout our analysis. Patents from 1873 onward allow us to gauge the typical lag between patent filing and issuance during the period we analyze. From 1873 through the end of our World War I sample, the average lag between filing and issuance was 1.2 years for the full set of technologies we analyze and just over 0.9 years for prosthetic devices.[11] We test whether indexing by patent issuance dates changes our findings relative to indexing by filing dates using data from the World War I era. We find that the time series for both our treatment and control classes are shifted forward by roughly one year when indexed by patent filing year, as shown in panels A and B of Figure C.1. This has little influence on our reading of the evidence.

Figure 1 provides an initial look at time series on prosthetic device patents and other broad categories of patents during the historical episodes we analyze. The dashed vertical lines in each panel encompass the years we subsequently associate with war-induced booms in prosthetic device patenting. It is quite clear from the panels of Figure 1 that both the Civil War and World War I were associated with substantial increases in the rate of prosthetic device patenting among combatant nations (i.e., the United States during the Civil War and World War I, the Confederacy during the Civil War, and the United Kingdom during World War I), but not among non-combatant nations (i.e., the United Kingdom during the U.S. Civil War and Spain during both the U.S. Civil War and World War I). However, quantifying the causal effect of wartime demand shocks requires constructing counterfactuals, which we discuss in section 4.

There are limitations when using patent counts to measure innovation. Primarily,

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[11]In the technology classes we analyze, the average lag between filing and issuance has exceeded three years during the 21st century. Lags between filing and issuance have thus been much longer in recent years than during our sample.

patent counts do not necessarily measure changes in meaningful innovation. Thus, during the period surrounding World War I, we follow standard practice in the literature by using citations as a proxy for patent quality. As shown in Panel B of Figure C.2, the average number of citations per patent was fairly stable during World War I, suggesting that the prosthetic device patent boom was associated with patents of similar impact as the pre-war patents. Citation measures of quality for Civil War patents are less reliable. As described by Berkes (2018), 19th-century patents have less complete and noisier citation data. Panel A shows that, during the Civil War period, the sparsity of citation data likely renders this exercise uninformative. To validate the quality of Civil War era patents, we look to information reported in Tables E.1 and 1, which we describe below in detail.

Several features of the Civil War period allow us to establish that changes in patenting connect to real industry responses. The most striking point is that we directly observe the entry of new manufacturers. Further, as reported in Table E.1, we are able to establish links from patents to manufacturers, from manufacturers to sales through May 1866, and from both sales and manufacturers to expert assessments of quality.[12] Twelve out of the thirteen most notable manufacturers of artificial legs and eight out of the nine most notable manufacturers of artificial arms from the Civil War period can be linked to at least one patent. Through May 1866, these patent-holding manufacturers accounted for nearly all of the artificial legs and nearly 90 percent of the artificial arms furnished to Union Army veterans. As shown in Table 1, contemporaneous sources reveal a dramatic increase in the number of artificial limb manufacturers, artificial limbs produced, and the total value of artificial limb output during the U.S. Civil War. Finally, medical histories

[12]A limitation of this analysis is that we can only estimate market shares for the 6,075 artificial limbs documented in Barnes and Stanton (1866). Because this memorandum was submitted on May 11, 1866, it cannot document market shares for artificial limbs delivered after that time.

document that these episodes were, in fact, episodes of substantial advance in artificial limb technologies.[13]

3.2 Coding Patent Attributes

Beyond measuring patent flows, our analysis aims to understand the economic attributes that are emphasized in each patent. We pursue this to understand how inventors distributed their efforts across improving aspects of production processes and/or particular dimensions of each product's quality. Because the data required for this analysis did not previously exist, we developed a novel data set.

Note that our novel data on patent attributes consists primarily of patents filed with the USPTO. Because we do not have the full texts of the Confederate patent documents, we cannot describe their detailed economic attributes. Additionally, we have not coded the attributes of Spanish patent documents due to language barriers and the fact that there are too few Spanish prosthetic device patents in our sample to generate reliable time series data. Finally, our coding of the attributes emphasized by British patents

[13]Post- and late-war rankings of artificial limbs by quality further support a link between quality and market share (Barnes, 1865; Houston and Joynes, 1866). The top three rated artificial legs accounted for just under 60 percent of sales through May 1866, while the top four rated artificial arms accounted for just over 60 percent of sales through May 1866. The highly-rated limbs with low market shares were those developed relatively late during the war, namely the artificial arms of John Condell and the National Arm and Leg Company. The low market shares we observe for these limbs in sales through May of 1866 are thus largely mechanical, as they were not on the market when most of the limb purchases for which we have documentation occurred. Low-rated limbs with non-trivial market share tended to be either unpatented or to involve pre-war patents, suggesting an incumbency advantage.

relies on key word searches rather than the methods discussed below.

Our data set on patents filed with the USPTO quantifies the economic attributes emphasized in historical patent documents. To generate this information, we first created a program to scrape historical U.S. patent documents from Google Patents. Using the text of each patent document, we then coded a set of product and/or production process attributes on which the patent places emphasis. We describe three of these attributes, namely cost, simplicity, and adjustability, as cost-oriented production process traits. That is, these traits involve aspects of a product's production. We use the term "adjustability," for example, to describe patents that emphasize uniform production of outputs that can subsequently be fitted (or "adjusted") to the needs of a specific consumer. Three traits, namely comfort, appearance, and occupation-oriented appliances, are quality-oriented attributes. We also code two additional traits, namely materials and durability, that we have not explicitly labeled as either product or production-process traits.

Table 2 presents a concise verbal definition of each economic attribute. The table also summarizes three important aspects of each attribute related to the quality of the information we capture with each variable. The first aspect, summarized in column 3, is the strength of the linkage between each trait and the hypotheses we have generated based on the historical record (i.e., the hypotheses laid out in section 2). The second aspect, summarized in column 4, is our assessment of the extent to which our text analysis procedure generated a variable that successfully captures the economic content we sought to capture.[14] The third aspect, summarized in column 5, is our assessment of the challenges associated with identifying comparison technology classes to construct control groups for our analysis of a given trait.

How successfully can the variables we generate capture the intended economic con-

[14]Considerations underlying these assessments are discussed in detail, with the aid of illustrative examples, in Appendix A.

tent of patents? A key point regarding this important methodological question is that the difficulty of identifying economic concepts in text can vary substantially from concept to concept. In the remainder of this section, we illustrate the underlying issues with a small number of examples. Appendices A and B provide substantially more detail.

Some economic concepts are straightforwardly conveyed in text. We found this to be true, for example, of the traits cost and simplicity. One patent, for example, describes the mechanism underlying an artificial knee joint as having "great simplicity, and therefore cheapness." A second states "The object of my invention is to imitate this eccentric motion of the knee-joint in the simplest manner." For both simplicity and cost, there is little difference between the performance of our close readings, our fully refined machine learning model, and a straightforward keyword search.

Other concepts are more difficult to track in text than cost or simplicity. Tracking new materials, for example, proved difficult because establishing a set of keywords requires knowing what materials are common and what materials are newly introduced in manufacturing products in a given technological class. These difficulties are sufficiently severe that we place little emphasis on our findings for the "materials" trait.

Other traits can capture clear and distinctive technological developments despite being very specific to a particular technological class. The trait we term "appliances" exemplifies this third scenario. As illustrated through a set of examples, occupation-oriented "appliances" were a critical, clearly defined dimension of prosthetic device innovation during World War I. This dimension of prosthetic devices, however, does not have a strong analogy in other technology classes. This fact casts doubt on the potential utility of constructing a control group for analyses of such a trait, as conveyed by our designation of appliances as "weak" in column 5 of Table 2. For a trait like "appliances," evidence from simple time series differences may be more informative than analyses that incorporate counterfactuals based on other technology classes.

3.3 Text Analysis

This section provides an overview of the text analysis tools we developed and implemented to describe the attributes of patents filed with the USPTO. Appendix B describes these tools in greater detail and underscores several best practices to consider when generating variables with machine learning algorithms.

Our approach to text analysis can be described as involving a keyword search that has been informed by domain-specific knowledge and enhanced by machine learning tools. We developed domain-specific knowledge by closely reading just over 1,200 patent documents. While reading these patents, we completed two tasks. First, we constructed the data set used to train our machine learning model by determining, on the basis of our close readings, whether each patent emphasizes specific attributes. Second, we construct the initial sets of keywords that we associate with each of the attributes.

The set of closely-read patents (i.e., the "training set") covers the domains relevant to our analysis. That is, our training set includes patents from both the prosthetic device class and candidate control classes, as well as from both the Civil War and World War I-eras. To achieve this coverage, we randomly selected our sample of closely-read patents after stratifying across technology classes and war episodes. As summarized in Table C.1, the manually coded data set contains 195 prosthetic device patents and 399 other medical or mechanical patents from the Civil War period, as well as 302 prosthetic device patents and 305 other medical or mechanical patents from the World War I period.[15]

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[15]The attribute "appliances" is an exception. The relevance of occupation-oriented appliances was drawn to our attention by a referee in August 2021, which was several years after we completed the close readings underlying the coding of other traits. Our coding of appliances is thus based on a keyword search that is informed by close readings of a smaller number of patents.

Our text analysis task faces a common problem of dimensionality. With just over 1,200 patents in our training set, algorithms will perform poorly if we attempt to use every word from every patent document as an input. We thus implement an approach to limit the algorithm's attention to the most relevant words, or "features," in each patent document's text.[16] The features we selected are a set of keywords, synonyms, and a small neighborhood of textual context surrounding the keywords and synonyms (see appendix B for more details). We developed our initial lists of keywords based on our 1,200 closely read patents. We next augment these keywords with synonyms that appear in similar linguistic contexts, which we selected using the "Word2Vec" algorithm (Mikolov, Sutskever, Chen, Corrado, and Dean, 2013). Finally, to aid our algorithm in identifying context-specific word meanings, we gather a "spread" of contextual words surrounding the appearance of each keyword. Our augmented set of keywords and their accompanying contextual "spread" are the features from each patent that we use as inputs into our machine learning model. After training and validating our model, we use the model to extend our encodings to roughly 750,000 patent texts that span our treatment and control groups.

As discussed in appendix B, a caveat accompanying our analysis is that seemingly modest reductions in the accuracy of our text analysis models can substantially attenuate our estimates of the effects of wartime procurement on the direction of prosthetic device innovation. While the accuracy of our models is generally quite high, it varies across the variables we construct. Moderately lower accuracy warrants caution, for example, in interpreting our analysis of the traits we term "materials" and "durability."

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[16]This approach, which is called "feature selection," has been shown to improve the efficiency of predictive models (Guyon and Elisseeff, 2003). The familiar Lasso procedure, for example, limits the number of features in the model by applying a penalty factor within its objective function.

3.4 Novel Data Set on Patent Attributes

Our final data set of patents filed with the USPTO, produced by our machine learning approach, describes the economic attributes of 745,558 patents, with the earliest coming from 1840 and the latest from 1940. There are 814 prosthetic device patents, 19,666 other medical patents, and 725,078 mechanical patents. Our regression analyses focus on samples of our 745,558 patents for which the patent year is in relatively close proximity to each conflict. These samples extend from 1855 to 1867 and from 1910 to 1922.

Across this large set of patents, appendix Table C.2 shows that the economic traits we coded are only modestly correlated with one another. The primary exceptions are cost and simplicity. Among prosthetic device patents, cost and simplicity share a correlation of 0.378 with an associated r-squared of 0.142. Similarly, across all patents in our data set these traits share a correlation of .303 with an associated r-squared of 0.092. Correlations across all other trait pairs are between -0.12 and 0.13, highlighting that the traits capture independent dimensions of innovation.

4 Empirical Strategy

We now present our specifications for analyzing changes in patenting rates and in the economic characteristics emphasized in patent documents. After presenting each estimation framework, we highlight the key challenges we face when attempting to generate causal estimates of the effects of wartime demand shocks.

4.1 Analyzing Patent Counts

We begin by estimating the effects of the Civil War and World War I on patent counts using the regression equations below. The first is specified as an Ordinary Least Squares model for predicting the log of patents per year:

$$ln(N_{t,c}) = \alpha_{c,w(t)} + \alpha_t + \beta_1 1\{\text{War}\}_t \times 1\{\text{Prosthetic}\}_c + \epsilon_{c,t}. \tag{1}$$

The second is specified as a Poisson model of patent counts:

$$E[N_{t,c}|X_t] = exp(\gamma_{c,w(t)} + \gamma_t + \beta_1 1\{\text{War}\}_t \times 1\{\text{Prosthetic}\}_c + \varepsilon_{c,t}). \tag{2}$$

In both equation (1) and equation (2), c denotes patent classes, t denotes time (multi-year time periods for these specifications), and $w(t)$ denotes war episodes (Civil War and World War I). $N_{t,c}$ denotes the number of patents in class c at time t. The specifications include time fixed effects (α_t or γ_t) and episode-by-patent class fixed effects ($\alpha_{c,w(t)}$ or $\gamma_{c,w(t)}$). The coefficient of interest is β_1, which is an estimate of the differential change in the patenting rate for prosthetic devices relative to the control classes during war episodes relative to pre-war periods. The periods over which the wars influenced prosthetic device patenting are defined to extend from 1862 to 1866 for the Civil War and from 1916 to 1922 for World War I.

The key challenge in developing causal estimates is to construct control groups that approximate the counterfactual development of patenting rates for prosthetic devices. Technology classes might generate inappropriate counterfactuals for a variety of reasons. They might, for example, be affected by very different sets of scientific developments (e.g., nuclear technology vs. prosthesis). Alternatively, a plausibly comparable technology class will be a poor control class if it is directly affected by wars (e.g., firearms) or if it is shaped by spillovers from prosthetic device innovation.

Our selection of a complementary set of control groups follows Finkelstein (2004), whose analysis of vaccine clinical trials is analogous to our setting in some key respects. The patents we use to construct control groups come from broad categories of medical and mechanical innovations. In all analyses, we exclude technology classes for which there was one or fewer patents per year within the time periods into which we divide the data. Our largest control group incorporates all medical and mechanical technology classes that meet this criterion. We also consider sub-groups chosen to either increase comparability or reduce the likelihood that the control group contains patent classes that could be directly affected by the wars. Like Finkelstein (2004), we also consider data-driven control groups. For our analysis of patent flows, the data-driven approach selects the control group to match baseline flows of prosthetic device patents in levels.

4.2 Analyzing Patent Traits

Our analysis of the traits emphasized by wartime prosthetic device patents confronts challenges that differ from the challenges facing our analysis of patent counts. The variables of interest in this analysis describe the share of patents within a given technology class (c) and time period (t) that emphasize the characteristic of interest:

$$\text{Trait Share}_{t,c} = \frac{\text{\# Patents with a Trait}_{t,c}}{\text{\# Patents}_{t,c}}.$$

For our analysis of patent traits, it is less clear what might constitute a reasonable control group. It may simply be less relevant, for example, to worry that the traits emphasized by prosthetic device patents will shift markedly for reasons unrelated to the wartime demand shocks on which our analysis focuses. As an initial estimator, this leads us to consider simple time series changes among prosthetic device patents:

$$\beta^{TS} = [\text{Trait Share}_{\text{wartime, prosthetics}} - \text{Trait Share}_{\text{pre-war, prosthetics}}] \tag{3}$$

This is captured by β^{TS} from equation (3).

We also consider difference-in-differences estimates, which net out changes in the emphasis on a given trait among the patents within a control group. For analyses of this sort, selecting control groups is non-trivial because some traits of interest are only relevant to a small set of the technology classes within our broadest control group. As shown in Table C.3, for example, this is true of traits including "appearance" and "comfort." This leads us to select control groups using several complementary approaches, which include the construction of synthetic control groups as well as a simple matching procedure.[17] We discuss additional aspects of our application of the synthetic control procedure in Appendix D. The resulting estimator takes the form below:

$$\begin{aligned}\beta^{DD} = &[\text{Trait Share}_{\text{wartime, prosthetics}} - \text{Trait Share}_{\text{pre-war, prosthetics}}] \\ &- [\text{Trait Share}_{\text{wartime, control classes}} - \text{Trait Share}_{\text{pre-war, control classes}}],\end{aligned} \tag{4}$$

We interpret our findings as being robust if we obtain similar results whether we rely on the time series variation, as in equation (3), or any of several plausible difference-in-differences strategies, as in equation (4).

Further, we highlight a key difference between dimensions of product quality and aspects of the production process. Dimensions of product quality can be highly context-specific, which makes it difficult to select control groups. Consequently, we have more confidence in our analyses of attributes that relate to the production process than in our analyses of attributes that capture dimensions of quality.

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[17] When implementing the synthetic control approach for our Civil War sample, patent flows for many technology classes were limited, including prosthetic devices. This makes the share of patents emphasizing a given trait highly volatile across the Civil War baseline when expressed at an annual frequency. For our baseline method, we thus match levels and trends in four-year moving averages. Our results are little changed by matching levels and trends on either three- or five-year moving averages.

5 Results

This section presents estimates of equations (1), (2), (3), and (4). Subsection 5.1 presents estimates of the effects of the Civil War and World War I demand shocks on flows of prosthetic device patents, while subsection 5.2 interprets the magnitudes. Subsections 5.3 and 5.4 present estimates of changes in the attributes emphasized in prosthetic device patents during the wartime patent booms relative to the pre-war periods.

5.1 Overall Patent Flows

Table 3 presents estimates of equation (1). The estimates presented across the columns differ exclusively with respect to the patent classes used as controls. The estimate in column 1 reveals that wartime changes in prosthetic device patenting were roughly 95 log points larger than changes in patenting in all other medical or mechanical patent classes. Columns 2 through 7 reveal that this estimate is only moderately sensitive to using subsets of the broader set of controls. The subsets include other categories matched based on baseline patenting rates (column 2), other medical categories only (column 3), the "miscellaneous" mechanical classes (column 4), metalworking mechanical classes (column 5), materials processing mechanical classes (column 6), and all classes except those that would be plausibly affected by wartime demand shocks (column 7).[18] The estimates range from 85 log points to 102 log points. Panels B and C reveal substantial increases in prosthetic device patenting during each war episode, with economically larger increases

[18]Our restriction of the control group to other medical technology classes (column 3), is similar to the approach taken by Moser, Voena, and Waldinger (2014) in their analysis of chemicals patenting. However, we obtain moderately smaller point estimates when using these control classes rather than a broader control group since some of the medical categories may have been affected by wartime demand shocks.

occurring during the Civil War than during World War I.

Appendix C provides additional evidence relevant for interpreting these findings. First, Table C.4 presents estimates of the Poisson model described by equation (2). Second, Figure C.3 presents an "event study" analysis, which provides evidence against the concern that wartime increases in prosthetic device patenting were driven by pre-existing trends. Third, Figure C.4 illustrates why, despite having only two class-by-time period treatment events, the wartime increases in prosthetic device patenting are nonetheless strongly statistically distinguishable from zero when we conduct inference using "randomization tests" (Imbens and Rosenbaum, 2005). Each observation underlying Figure C.4's histograms represents the change in patenting in a patent class in our broadest control group. The dashed vertical lines are placed at the value of the change for prosthetic devices. In the Civil War histogram (Panel A), the change in prosthetic device patenting is the rightmost point in the distribution; this underlies the uniformly low p-values in Panel B of Table 3. The change during World War I is quite close to the right end of the distribution (Panel B). Figure C.5 presents the results of the randomization inference procedures we implement, which are described in greater detail in the appendix.

Readers may wonder about the rapid pace with which patent counts and evolved during the historical episodes we analyze. An anecdote may help to confirm that the responses we track are real. James Hanger, a renowned prosthetic limb inventor, is documented to have invented and produced a prosthetic limb within six months of being injured during the Civil War's initial skirmishes.[19] Hanger, Inc., the company he subsequently founded, remains in operation today. Beyond this setting-specific anecdote, the tendency for large shocks to generate rapid innovative responses has been observed elsewhere. Hanlon (2015) finds, for example, that the British textile industry responded

[19]Consistent with the systematic analyses of patent traits that we present below, Hanger's invention entailed improvements to both function and comfort.

quite rapidly to the Civil War's impact on its supply chains. More recently, Agarwal and Gaule (2022) find that the COVID-19 pandemic has had a much greater and more rapid impact on innovation than long-run elasticity estimates would lead one to predict.

5.2 Interpreting Magnitudes

The estimates in Tables 3 and C.4 capture the short-run responsiveness of patent flows to large shocks to market size. The magnitudes of both the shock and industry response are more readily translated into elasticities in the context of the Civil War than in the context of World War I.[20] Between data from Barnes and Stanton (1866), Hasegawa (2012), and the 1860 Census of Manufacturers, we can infer that the Civil War elevated annual revenues across the artificial limb industry by an average of roughly 100 log points over four years.[21] The estimates in Panel B of Table 3 thus suggest that, during

[20]Inferring elasticities during World War I faces additional conceptual hurdles and data limitations. The conceptual hurdle is that the conflict's global nature makes it difficult to infer the markets to which the firms were responding. The data limitation is that we lack sources on the number of manufacturers either during or preceding the war. In the 1910 Census of Manufacturing, artificial limb manufacturers are merged with a broader category of surgical appliances.

[21]The 1860 Census of Manufacturing reports the value of the industry's output as roughly $53,000 in 1859. From Barnes and Stanton (1866), we know that over the first four years of the Union Army's artificial limb program, an average of roughly $91,000 in artificial limbs were procured. Viewing this as an increase over baseline demand from causes outside of the war, we estimate a 100 log point increase by comparing $ln(53,000)$ to $ln(53,000 + 91,000)$. The increase in units sold exceeded the increase in revenues because the Civil War limb allowances were substantially lower than pre-war prices.

the Civil War, the elasticity of short-to-medium run patenting with respect to the short-to-medium run shock to potential revenues was slightly greater than 1. We can similarly infer an elasticity of firm entry with respect to the Civil War era demand shock. As reported in Table 1, there were five artificial limb manufacturers in the 1860 Census of Manufacturing, and at least 17 manufacturers in 1865, implying an increase of at least 120 log points. This implies an elasticity of firm entry of greater than 1. These elasticity estimates are larger than typical estimates of the long-run effects of potential market size on innovation, as discussed by Dubois, De Mouzon, Scott-Morton, and Seabright (2015). Consistent with recent findings from Agarwal and Gaule (2022), who analyze the COVID-19 context, we find relatively sharp short-run responses of innovation to crisis-driven demand shocks.

Interestingly, wartime booms in prosthetic device patenting were not sustained over the long run. This might initially seem puzzling, given that the government's commitment to providing limbs was ongoing. Historical context provides evidence, however, that sustained demand for U.S.-manufactured prosthetic limbs was short-lived during both episodes. Following World War I, demand for U.S.-manufactured devices was short-lived because the European powers made conscious efforts to develop their own prosthetic device industries. By 1920, moreover, veterans with amputated limbs in Germany, Canada, and the United States were documented to prefer adapting to life without a prosthetic (Linker, 2011, p. 114,118). The same was true following the Civil War; an overwhelming majority of Union veterans chose cash over replacement artificial limbs when they were given that choice during the post-war years. Substantial demand for replacement limbs thus may not have materialized. In both settings, the preference for cash over replacement limbs is suggestive that, contemporaneous innovation notwithstanding, quality remained low in an absolute sense.

5.3 Traits of Wartime Prosthetic Device Patents

We now turn to estimating the effects of wartime procurement on the economic characteristics of prosthetic device patents. Our estimates of equations (3) and (4) are presented in Table 4, while the underlying time series are presented in Figures 2 and 3, with additional detail in Appendix Figures C.6, C.7, C.8, C.9, and C.10. Several facts of interest emerge from this analysis.

We find that the Civil War was associated with across-the-board increases in emphasis on our cost-oriented production process traits. The average across these traits (namely "cost," "simplicity," and "adjustability") more than doubled from a base of 0.16, as shown in Figure 2. This estimate is statistically distinguishable from zero at the 0.01 level using either the simple time series or synthetic control estimator, as it is a true outlier relative to the distribution of randomization test outcomes. In contrast, the average across cost-oriented production process traits moved quite modestly during World War I. While both periods ushered in substantial increases in emphasis on adjustability, Civil War-era prosthetic device patents also exhibit economically substantial shifts towards emphases on "cost," and "simplicity" as shown in Figure 3. Changes in the latter two traits were relatively modest during the World War I episode, as can be seen in Appendix Figure C.7. This contrast is plausibly linked to procurement incentives, as the low, fixed-price reimbursements of the Civil War period created strong incentives for innovation to reduce costs. While we do not know the precise details of World War I procurement arrangements for artificial limbs, cost-plus contracts, which blunt incentives for innovation to reduce costs, were "the most common type of contract" during that period (Graske, 1941, p. 17).[22]

[22]Withrow Jr (1942) links the predominance of cost-plus contracts during the World War I-era to the reluctance of firms to submit bids on a fixed-price basis given the risks

A comparison between patents for artificial arms and legs provides an additional, suggestive piece of evidence that the emphasis of Civil War era prosthetic device patents on production processes can be linked to the Union's procurement policy. The government's procurement arrangement, namely fixed-price reimbursement of $50 per arm and $75 per leg (roughly $1,000 and $1,500 in 2018 dollars), created a strong incentive for cost-oriented production process innovation because these payments were modest relative to manufacturers' costs. Cost data from the 1860 manufacturing census indicates that payments for artificial arms implied a lower charge-to-cost ratio than for artificial legs (roughly 2/3 vs. 3/4), creating an even greater incentive for cost-reducing innovation. As shown in Figure C.11, patents for artificial arms did indeed exhibit a more dramatic increase in their emphasis on production process improvements, and in particular on cost reduction, in comparison with patents for artificial legs.

An alternative possibility is that the emphasis of Civil War era artificial limb patents on the production process might simply have reflected the industry's natural trajectory. That is, if artificial limbs were a "new" technology during the pre-war period, a surge in production-process innovation might naturally be expected. This is not plausible, however, as the pre-war state-of-the-art technology had existed for quite some time. Patents held by Benjamin Franklin Palmer, the pre-war artificial limb industry's leading manufacturer, extended back to 1846. Throughout the 1850s, the rate of production process innovation evolved quite smoothly for artificial limb patents as well as for patents in our control groups. The early-1860s spike in production process innovation for artificial limbs is a distinctive break from this pattern.

We next consider dimensions of quality, for which two findings are both empirically robust and connect directly to historical narratives. First, both our simple time series and

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associated with rapidly rising prices for raw materials.

synthetic control estimators provide evidence that World War I-era patents exhibit an increase in emphasis on occupation-oriented appliances (see Table 4 and Figure 3). This finding has a strong connection to the historical records regarding both the intentions of World War I-era artificial limb procurement and the specific technologies to which this period's patents gave rise. Regarding the specific technologies, these "appliances" involved interchangeable, occupation-oriented attachments like the hammer, welding, and woodwork oriented attachments shown in Figures A.4, A.5, and A.6 in appendix A. Notably, as shown in column 5 of Table 4, British World War I-era patents offer a strong piece of supplemental evidence that the demand associated with employment-oriented rehabilitation programs generated increases in emphasis on occupation-oriented appliances.[23] This is relevant in part because the shift towards occupation-oriented appliances in the U.S. patents is, despite representing a substantial increase in percent terms, not an outlier within the relevant placebo distribution and is thus on the margins of statistical significance.

Second, both our simple time series and synthetic control estimators yield strong evidence that Civil War-era prosthetic device patents exhibit a substantial increase in emphasis on comfort (see Table 4 and Figure 3). By contrast, World War I-era prosthetic device patents de-emphasized comfort (see Table 4 and Figure 3). These findings are plausibly linked to shifts in demand, which came directly from veterans during the Civil War and from the veterans' medical bureaucracy during World War I. Of course,

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[23]Note that the historical British patents had to be categorized on the basis of subject matter indices that do not map cleanly into the USPTO's technology classification system. While it was straightforward to identify "artificial limb" patents, we did not have a mapping from the subject matter indices into the control classes we utilize in the U.S. patent data. Consequently, our analysis of the traits emphasized by British patents does not include a difference-in-differences style estimate.

such a difference in innovation across wars may reflect a variety of factors aside from those that we identify. The historical record, however, as discussed in section 1, suggests that the World War I-era medical bureaucracy played a heavy hand. Our findings for this period are very much in line with the bureaucracy's de-emphasis on the veteran's comfort and emphasis on social and labor market reintegration. As with our evidence on occupation-oriented appliances, British patents offer supplemental evidence on the decrease in emphasis on comfort during the World War I period.

5.4 Robustness of Analysis of Patent Traits

In section 4, we discussed the challenges underlying the construction of control groups in our analysis of the product and production process traits emphasized in patent documents. These challenges motivated our presentation of both a simple time series estimator and a synthetic control estimator in Table 4. In this section, we present an additional robustness analysis in which we deploy a range of alternative procedures for constructing control groups. Tables C.5, C.6, C.7, and C.8 present difference-in-differences estimates using the following approaches: Table C.5 relies exclusively on our full sample of 1,200 manually coded patents; Table C.6 uses the full sample of patents as coded using our machine learning model; Table C.7 restricts the control group to medical patent classes; finally, Table C.8 selects control groups using a simple "caliper" matching procedure.[24]

The results we have emphasized throughout are findings that are robust to deploying this full set of strategies for constructing control groups, as well as to relying exclusively

[24]In yet another robustness check, we have constructed synthetic controls from a sample of medical and mechanical technology classes that excludes all classes that might be directly affected by wars, which also has very little effect on our estimates.

on the time series change in the emphases of prosthetic device patents as in equation (3). These include our findings on the Civil War-era increase in emphasis on production process innovation, the Civil War-era increase in emphasis on comfort, the World War I-era decrease in emphasis on comfort, and the World War I-era increase in emphasis on occupation-oriented appliances. In each of these cases, our estimates are robust across the full range of strategies for constructing control groups and imply large percent changes in emphasis on the trait in percent terms.

In contrast with the robust evidence on the findings discussed above, our evidence on appearance and durability illustrate methodological challenges in the analysis of patent texts. The estimates in Tables 4, C.5, C.6, C.7, and C.8 reveal that our estimates for appearance and durability, and to a lesser extent materials, are sensitive to whether we look to the simple time series change, use the full set of candidate controls, or use a data-driven control group. As we discuss in greater detail in appendices A and B, these traits pose challenges with respect to both the construction of control groups and the implementation of text analysis methods. Consequently, we interpret our evidence on appearance, durability, and materials as weak. Our conclusions thus emphasize the traits for which our evidence is robust and for which we have greatest confidence in the output from our text analysis methods.

6 Discussion and Conclusion

Our analysis of Civil War and World War I-era prosthetic device patenting yields several findings of potential interest. First, we find that wartime procurement programs were associated with large increases in the volume of prosthetic device patents. We thus add to an existing body of evidence that finds that innovation can respond quite strongly to changes in demand.

Second, we find that cost-conscious production process innovation increased substantially during the Civil War. This highlights the potential relevance of the Civil War period's procurement model, which involved fixed-price reimbursement at modest rates. Experts observe that modern medical innovations have tended to bring costly enhancements to quality rather than cost-conscious improvements in productivity (Chandra and Skinner, 2012; Skinner, 2013). Our findings provide a useful counter-example to this tendency. Demand shocks coupled with cost-conscious payment models can steer innovation in a cost-conscious direction.

Third, we find that the prosthetic device patents of the Civil War and World War I episodes diverged with respect to dimensions of quality. In contrast with World War I-era patents, Civil War-era prosthetic device patents exhibited an increase in emphasis on comfort. Additionally, World War I-era prosthetic device patents emphasized occupation-oriented "appliances," as illustrated by the hammer, welding, and woodwork attachments that appear in appendix Figures A.4, A.5, and A.6. These differences are plausibly linked to a World War I-era shift in choice away from veterans and towards medical professionals. This shift was associated, in turn, with a heightened emphasis on veteran rehabilitation and re-employment. As a caveat, we note these differences between Civil War and World War I-era prosthetic device innovations may stem from several factors that would be difficult to empirically disentangle.

We conclude by reflecting on the role of innovation in enabling individuals and societies to respond to large and negative health shocks. Both wars and pandemics can have dramatic effects on the need and demand for medical innovations. Our analysis adds to a body of research on how innovation responds to these societal needs. While the overall consequences of wars and pandemics are devastating, the evidence reveals how their adverse effects can be blunted by the ingenuity of inventors and entrepreneurs.

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Patent Time Series For Regions That Were Vs. Were Not Directly Impacted by the US Civil War and World War I

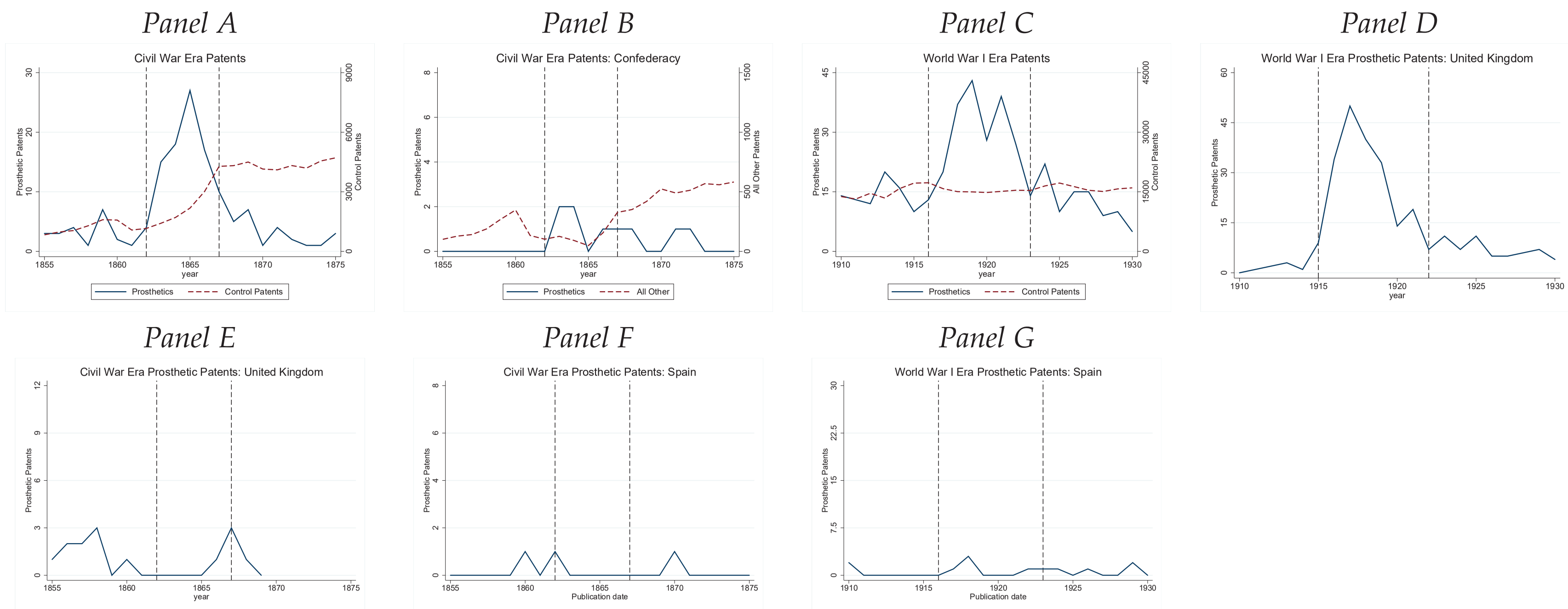
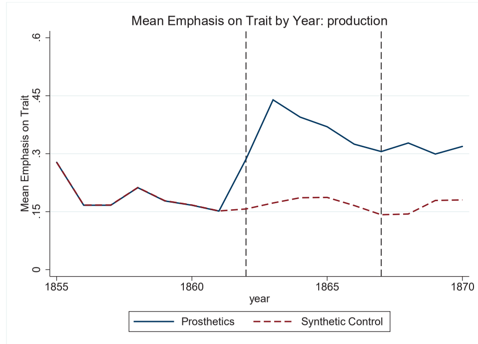


Figure 1: **Patent Time Series.** Note: This figure presents annual time series on patents, using USPTO data from Berkes (2018), data from the Confederate patent office as documented by Dobyns (1994) and Knight (2011), as well as data on British and Spanish patents. Dashed vertical lines indicate the periods we associate with wartime prosthetic device patenting in the United States (1862 to 1866 during the Civil War and 1916 to 1922 during World War I) or in Britain (1915 to 1922 during World War I). In USPTO data, the solid blue line corresponds with patents from USPTO class 623 "Prosthesis." The four Confederate prosthetic device patents were identified by the authors based on patent titles. British and Spanish patents were categorized as prosthetic device patents using subject matter indices. In panels using USPTO data, red dashed lines correspond with all other medical and mechanical patent classes, defined using the hierarchical structure of technological categories in the NBER Patent Database (Hall, Jaffe, and Trajtenberg, 2001).

Changes in the Averages across Production and User-Oriented Traits

Panel A



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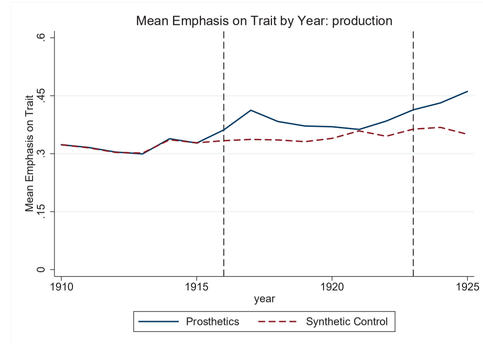

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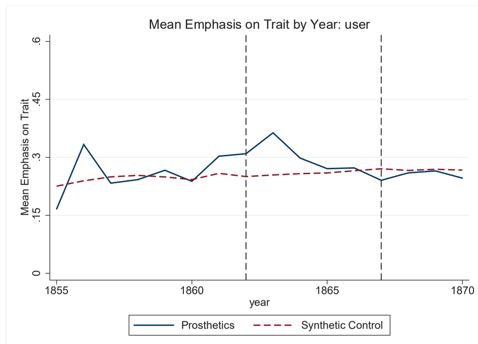


Panel D

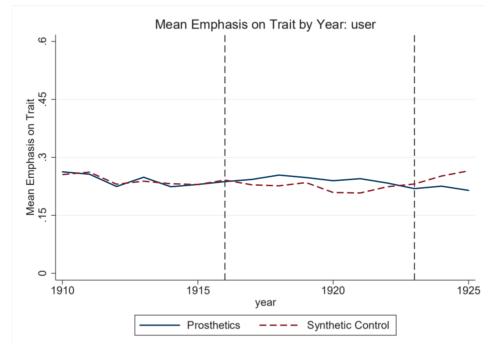
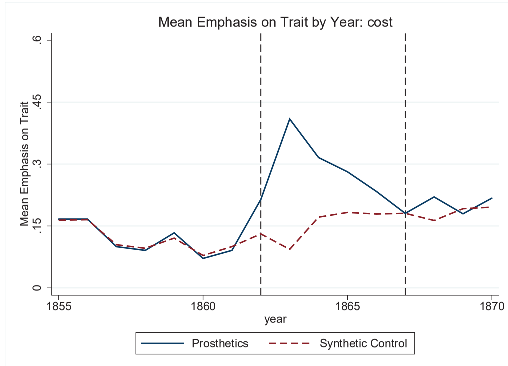


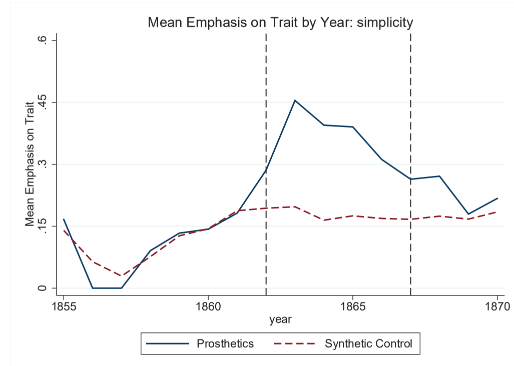
Figure 2: **Changes in the Averages across Production and User-Oriented Traits.** Note: The figure presents data on "treatment" and "synthetic control" series that describe the evolution of patents' emphases on averages across trait aggregates we term "production" (a simple average across "cost," "simplicity," and "adjustability") and "user" (a simple average across "appliances," "appearance," and "comfort") traits. The time series in Panels B and D are calculated as 4-year moving averages. The bar charts in Panels A and C present averages of the "Prosthesis" and "Synthetic Control" series. The series plot the share of patents in a given class ("Prosthesis" or the "Synthetic Control") that emphasize a given trait. In Panels A and C, the "Pre War" baseline extends from 1855 to 1861, and the "Wartime" period extends from 1862 to 1866. In Panels B and D, the "Pre War" baseline extends from 1910 to 1915, and the "Wartime" period extends from 1916 to 1922. We generate the synthetic control group using the "synth" package written by Abadie and Hainmueller (2010). "Donor weights" for panels A and C are chosen to match the treatment group on values extending from 1855 to 1861. "Donor weights" for panels B and D are chosen to match the treatment group on values extending from 1910 to 1915.

Changes in Traits with Strongest Connections to the Historical Record

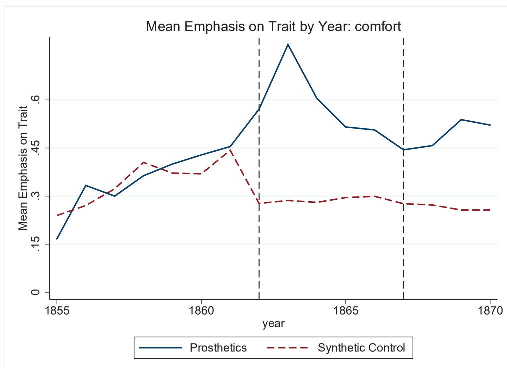
Panel A



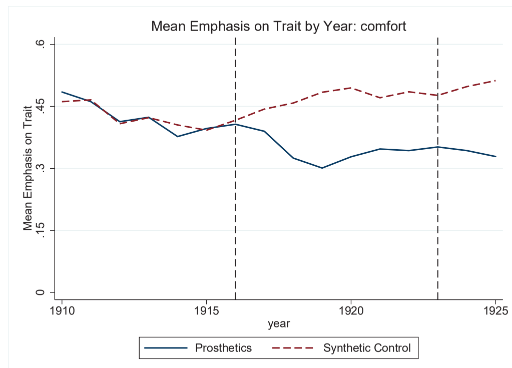
Panel B



Panel C



Panel D



Panel E

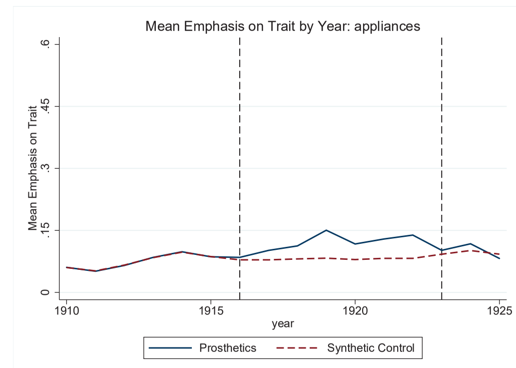


Figure 3: **Changes in Traits with Strongest Connections to the Historical Record.** Note: The figure presents data on "treatment" and "synthetic control" series that describe the evolution of patents' emphases on traits we term "cost," "simplicity," "comfort," and "appliances." The time series in Panels B and D are calculated as 4-year moving averages. The bar charts in Panels A and C present averages of the "Prosthesis" and "Synthetic Control" series. The series plot the share of patents in a given class ("Prosthesis" or the "Synthetic Control") that emphasize a given trait. In Panels A and B, the "Pre War" baseline extends from 1855 to 1861, and the "Wartime" period extends from 1862 to 1866. In Panels C and D, the "Pre War" baseline extends from 1910 to 1915, and the "Wartime" period extends from 1916 to 1922. We generate the synthetic control group using the "synth" package written by Abadie and Hainmueller (2010). "Donor weights" for panels A and B are chosen to match the treatment group on values extending from 1855 to 1861. "Donor weights" for panels C and D are chosen to match the treatment group on values extending from 1910 to 1915.

Table 1: **Facts on Industry Response Surrounding the Civil War**

	(1859)	(1865)	(1869)
Manufacturing Establishments	5	$\geq$ 17	24
Artificial Limb Output	$\approx$ 350	$\geq$ 3,461	$\approx$ 1,000-2,000
Value of Output	$53,000	$\geq$ $223,550	$166,416
Patents in Surrounding 5 Years	15	87	27

Note: Data for 1865 come from Barnes and Stanton (1866) and Hasegawa (2012). Other years come from Census of Manufacturing tabulations. Patent dates come from Berkes (2018).

Table 2: **Patent Attributes with Descriptions**

(1) Attribute	(2) Description	(3) Narrat.	(4) Interp.	(5) Controls
Individual Traits				
Cost	Construction is cheap, economical, and less labor intensive	Strong	Strong	Strong
Simplicity	Device construction is simple and less complex/difficult	Strong	Strong	Strong
Adjustability	Manufactured product adaptable to user specifications	Moderate	Weak	Strong
Materials	Made from new materials, substances, and compositions	Weak	Weak	Weak
Durability	Product is able to withstand wear and damage	Weak	Weak	Moderate
Appearance	Natural appearance, life-like, tasteful, and neat	Moderate	Strong	Weak
Comfort	Device noted as comfortable, noiseless, and promoting circulation	Strong	Moderate	Weak
Appliances	Attachable artificial limb components that aid in workplace tasks	Strong	Weak	Weak
Aggregate Traits				
Production	Combination of simplicity, cost, and adjustability traits			
User	Combination of comfort, appearance, and appliances traits			

Note: The table describes the definitions we apply in coding the economic attributes we analyze. Columns 3–5 offer our assessments of the relative strengths of the historical narratives, economic interpretations, and control groups for each trait, respectively. By "strong" historical narratives, we mean that there is ample historical evidence that contemporaneous economic factors drove an emphasis on the given trait during one or both wars. By "strong" economic interpretation, we mean that a trait can be cleanly linked to aspects of labor productivity, buyer desires, or mass production. By "strong" control groups, we assess that the keywords describing the given trait have similar meanings and rates of use in control classes as in the prosthetic limb class.

Table 3: **Relative Increases in Prosthetic Device Patenting During the Civil War and World War I**

	(1) All Cntrls	(2) Matched	(3) Medical	(4) Misc. Mech.	(5) Metal	(6) Mater. Proc.	(7) Non War
Panel A: Full Sample							
Prosthetics x War	0.951***	0.853***	0.981***	0.883***	1.015***	1.021***	0.945***
	(0.267)	(0.298)	(0.294)	(0.194)	(0.269)	(0.338)	(0.255)
N	432	88	34	128	56	92	362
Panel B: Civil War							
Prosthetics x War	1.216***	1.128***	1.259***	1.071***	1.260***	1.348***	1.198***
N	188	56	14	56	24	42	156
Panel C: WWI							
Prosthetics x War	0.687**	0.571	0.716***	0.697**	0.774***	0.698***	0.693**
N	244	32	20	74	34	52	208

Note: The table presents estimates of equation (1). The control group used for each regression is described in the column heading. The sample for Panel A includes both the Civil War and World War I episodes, while the sample for Panel B is from the Civil War episode and for Panel C is from the World War I episode. For the Civil War, the pre-war period extends from 1855 to 1861, while the period over which the war influenced prosthetic device patenting extends from 1862 to 1866. For World War I, the pre-war period extends from 1910 to 1915, while the period over which the war influenced prosthetic device patenting extends from 1916 to 1922. In Panel A, the standard errors reported in parentheses allow for clusters at the patent class-by-war episode level. ***, **, and ** indicate p-values less than 0.01, 0.05, and 0.1, respectively as calculated using a randomization inference procedure along the lines recommended by Imbens and Rosenbaum (2005). Additional details are reported in the main text.

Table 4: **Changes in the Nature of Prosthetic Device Patents**

	(1)	(2)	(3)	(4)	(5)	(6)
	US Civil War		US WWI		GB WWI	Notes
	Simple Diffs	Synth Estimate	Simple Diffs	Synth Estimate	Simple Diffs	
Panel A: Agg. Traits						
Production Average	0.187	0.190	0.074	0.038	0.124	Civil War Narrative (+)
	(0.000)	(0.000)	(0.008)	(0.049)		
	[0.000]	[0.000]	[0.016]	[0.098]		
User Average	0.006	0.036	-0.007	0.019	-0.109	
	(0.330)	(0.054)	(0.139)	(0.115)		
	[0.660]	[0.108]	[0.279]	[0.230]		
Panel B: Ind. Traits						
Cost	0.152	0.141	0.079	0.050	0.028	Civil War Narrative (+)
	(0.032)	(0.054)	(0.074)	(0.066)		
	[0.064]	[0.109]	[0.148]	[0.131]		
Simplicity	0.238	0.195	0.043	-0.001	0.226	Civil War Narrative (+)
	(0.032)	(0.011)	(0.254)	(0.557)		
	[0.064]	[0.022]	[0.508]	[0.990]		
Adjustability	0.171	0.076	0.099	0.116	0.118	
	(0.000)	(0.143)	(0.016)	(0.008)		
	[0.000]	[0.286]	[0.033]	[0.017]		
Appliances	0.049	NA	0.065	0.038	0.112	WWI Narrative (+)
	(0.106)		(0.049)	(0.066)		
	[0.213]		[0.098]	[0.131]		
Comfort	0.150	0.303	-0.119	-0.116	-0.230	WWI (-) and Civil War (+) Narratives
	(0.032)	(0.016)	(0.000)	(0.000)		
	[0.064]	[0.033]	[0.000]	[0.000]		
Appearance	-0.182	0.078	0.033	0.068	-0.209	
	(0.043)	(0.037)	(0.107)	(0.008)		
	[0.085]	[0.074]	[0.213]	[0.016]		
Durability	0.016	0.149	0.064	0.025	0.102	
	(0.372)	(0.083)	(0.041)	(0.172)		
	[0.745]	[0.167]	[0.082]	[0.344]		
Materials	0.026	0.035	0.008	-0.005	-0.050	
	(0.138)	(0.104)	(0.328)	(0.496)		
	[0.277]	[0.209]	[0.656]	[0.990]		

Note: Estimates in columns labeled "Simple Diffs" are of β^{TS} from equation (3), while estimates in columns labeled "Synth Estimate" are estimates of β^{DD} from equation (4), where the control group is constructed separately for each trait using the synthetic control procedure described in greater detail in the main text. One-sided p-values are presented in parentheses beneath each point estimate, and two-sided p-values are presented in brackets. Column 6 indicates instances in which the historical narrative delivers one-sided predictions. All p-values are generated using randomization inference (Imbens and Rosenbaum, 2005), which in this application involves straightforwardly ranking the point estimate for the prosthetic device technology class against within the "placebo" distribution of estimates for other technology classes.