Necessity is the Mother of Invention: Input Supplies and Directed Technical Change*

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Abstract

This study provides causal evidence that a shock to the relative supply of inputs to production can (1) affect the direction of technological progress and (2) lead to a rebound in the relative price of the input that became relatively more abundant (the strong induced-bias hypothesis). I exploit the impact of the U.S. Civil War on the British cotton textile industry, which reduced supplies of cotton from the Southern U.S., forcing British producers to shift to lower-quality Indian cotton. Using detailed new data, I show that this shift induced the development of new technologies that augmented Indian cotton. As these new technologies became available, I show that the relative price of Indian/U.S. cotton rebounded to its pre-war level, despite the increased relative supply of Indian cotton. This is the first paper to establish both of these patterns empirically, lending support to the two key predictions of leading directed technical change theories.

KEYWORDS: Directed Technical Change, Induced Innovation, Strong Induced Bias.

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1 Introduction

Directed technical theories suggest that a shift in the relative supply of inputs to the production process can influence the direction of technological progress (Hicks (1932), Acemoglu (2002, 2007)). In some cases, a change in the relative supply of inputs can encourage innovation that augments the relatively more abundant input, generating a positive relationship between the relative quantity and relative price of inputs. For example, it has been suggested that the increase in skilled workers in the U.S. starting in the 1970s caused skill-biased directed technical change, and that this directed technical change allowed the skill premium to increase despite the increase in the relative abundance of skilled workers (Acemoglu (1998), Kiley (1999)).[1]

Despite the interest in this theory, there has been relatively little documentation of the actual process of directed technical change and its impact on the market prices of inputs. This paper provides the first well-identified study of the impact of a shift in relative input supplies on both (1) the direction of technological progress and (2) relative input prices. To do so, it exploits a large exogenous shift in relative supplies to the British cotton textile industry caused by the U.S. Civil War (April 1861 - April 1865). The war, which included a blockade on Southern shipping by the Union Navy, sharply increased the cost of supplying U.S. cotton from the South. The result was a sharp depression in the industry; output dropped by as much as 50% and hundreds of thousands of mill operatives found themselves out of work or working short-time. The shortage of U.S. cotton forced British producers to turn to raw cotton from alternative suppliers, chiefly India. However, the cotton available from India differed from American cotton in important ways; it was a low-quality variety that was difficult to clean and prepare for the spinning process. Thus, this event generated a sharp shift in the relative supplies of two similar, but not identical, inputs to the production process. Historians and contemporary observers have noted the important changes that took place as a result of this event. D.A. Farnie, in his authoritative history of the British cotton textile industry, writes, "The shortage of American

[1]Other applications include the impact of labor scarcity on development in economic history (Habakkuk (1962), Allen (2009)), the sources of cross-country productivity differences (Acemoglu & Zilibotti (2001), Caselli & Coleman (2006)), the impact of high energy prices on energy-saving innovation (Newell *et al.* (1999), Popp (2002)), the effect of environmental regulation (e.g., Acemoglu *et al.* (2012)), the impact of immigration on technology upgrading (Lewis (2011)), and agricultural productivity trends (Hayami & Ruttan (1970), Olmstead & Rhode (1993)).

cotton compelled employers to re-equip their mills in order to spin Surat [Indian cotton], and especially to improve their preparatory processes...The reorganization of the preparatory processes entailed such an extensive investment of capital that it amounted almost to the creation of a new industry..."[2]

The first contribution of this paper is to document the pattern of directed technical change generated by the shock to input supplies. Using detailed new patent data, I show that the Civil War time period was characterized by a sharp increase in innovation in three types of cotton textile machinery – gins, openers/scutchers, and carding machines – that were particularly important for addressing the key bottlenecks in the use of Indian cotton. Comparing these three technology types to all other cotton spinning technologies, I document substantial increases in innovation in technologies related to the use of Indian cotton. Innovators reacted quickly, introducing simple improvements in technologies during the first year of the war, followed by more advanced machines in later years. Innovation in technologies related to Indian cotton peaked three years into the conflict, and remained high one to two years after the end of the war. Thus, the patent data reveal substantial directed technical change towards technologies that augmented Indian cotton.

To support these results, I draw on two additional indicators of technological progress. First, using data from one of the largest textile machine manufacturing firms of the period, Dobson & Barlow, I show the rapid evolution in technology over this period. This company cycled through four different gin designs in just four years, with the introduction of new designs often closely following the filing of a patent for gin technology. This suggests both the speed at which technology was changing as well as the link between patents and machine production. Second, I present data on one aspect of aggregate productivity: the amount of waste generated in the cotton textile production process. A simple calculation suggests that the waste generated when using Indian cotton fell by 19-30 percent between 1862 and 1868, consistent with the impact we should expect from the new technologies, many of which were designed specifically to reduce waste.

[2]Farnie (1979), p. 152-153. Contemporary observers also noted these changes. Ellison (1886) writes, "The high prices caused by the cotton famine, however, gave an impetus to the culture [of cotton] in India which it would not otherwise have obtained, and thereby secured to Europe a permanent increase in supply. Moreover, the quality of the cotton has been so materially improved by the introduction of better methods of handling the crop, that 'Surats' are no longer despised as they were up to within a few years ago."

The second contribution of this paper is to provide evidence that an increase in the relative supply of one input (Indian cotton) can affect the relative price of that input through directed technical change. In the absence of directed technical change, we would expect the relative price of an input to fall as it becomes relatively more abundant. On the other hand, directed technical change may offset this, by shifting relative demand for the more abundant variety upward enough to offset the shift in relative supply. Acemoglu calls this result the "strong induced-bias hypothesis." To look for this pattern, I collected new data on the prices of several cotton varieties from *The Economist* magazine. Graphing the relative price of Indian to U.S. cotton, I observe a sharp decrease following the onset of the war.By early 1862 the relative price of Indian cotton had reached its lowest point in the 1855-1876 period. However, starting in late 1862 the relative price of Indian/U.S. cotton rebounded, and it then remained at or above its pre-war level through 1874, despite the fact that it had become much more abundant relative to U.S. cotton. The timing of this rebound follows the introduction of many of the new technologies tailored to the use of Indian cotton. This evidence is consistent with the strong-induced bias hypothesis.

To strengthen this result, I control for time-varying factors using the price of two smaller alternative cotton varieties from Brazil and Egypt. Contemporary reports indicate that these varieties were too small to warrant substantial new innovation during the Civil War. But, like Indian cotton, they became much more abundant relative to U.S. cotton during the war. Thus, these varieties provide an indicator of how relative price might have behaved in the absence of directed technical change. In contrast to the pattern observed for Indian cotton, the relative price of Brazilian/U.S. cotton and Egyptian/U.S. cotton remained low during the period in which the relative supply of these varieties was high, exactly as we would expect in the absence of directed technical change. This suggests that the pattern observed for Indian cotton was not the result of other shifts occurring during the Civil War.

A relatively small number of existing empirical studies provide evidence on the relationship between input supplies (or prices) and the direction of technological progress. The main focus of this research has been on the energy sector, where studies by Newell *et al.* (1999), Popp (2002), and Aghion *et al.* (2012) look at the impact of high energy prices on energy-saving innovation.[3] The current study differs from

[3]An alternative approach to directed technical change is taken by Blum (2010) who uses cross-country trade data in an effort to find evidence of directed technical change at a macro level.

previous work in two ways. First, my identification of the impact of shifting input supplies on innovation is arguably cleaner because I am able to take advantage of a large, exogenous, and surprising shock to input availability. This is aided by the fact that there was virtually no government intervention in this market due to the strong free-market ideology that was dominant in Britain during this period. Second, this is the first study to evaluate the strong induced-bias hypothesis. Previous researchers have used input prices as the key explanatory variable, so they were not able to look at the impact of technological change on input prices. This project is also related to work considering the impact of input supplies on the adoption of already-existing technologies, such as Lewis (2011) and Acemoglu & Finkelstein (2008).

The next section provides a brief review of the theoretical motivation behind this study, while Section 3 introduces the empirical setting. The data are described in Section 4, followed by the empirical analysis in Section 5. Section 6 concludes.

2 Motivating theoretical framework

This project is motivated by directed technical change theories, and in particular the model offered by Acemoglu (2002). This section provides a brief review of the key elements and predictions of this theory. The theory focuses on an industry with two inputs and delivers three main results. First, if the relative expenditure level on an input increases, the relative technology level of that input should also increase on the balanced growth path. Second, an increase in the relative supply of an input will increase the relative technology level of that input on the balanced growth path if the elasticity of substitution between inputs is sufficiently high (> 1). Third, an increase in the relative supply of an input will increase the relative price of that input on the balanced growth path when the elasticity of substitution between inputs is sufficiently high (> 2).

The model is dynamic in continuous time, but for simplicity I suppress the time

While this study is focused on the impact of changes in input supplies on innovation, there are complementary studies that consider the influence of demand factors or competition. Finkelstein (2004) and Acemoglu & Linn (2004) consider the impact of shifting demand patterns on innovation rates in the context of the pharmaceutical industry. Both find that shifts in demand can be an important driver of new product development. For competition, Bloom *et al.* (2011) use several measures of technical change, including patents and R&D expenditures, to show that an increase in competition from Chinese producers led European firms to upgrade their technology.

notation. Consumption is over a CES index of two final goods. For the purposes of this study, we can think of these as textile goods made using U.S. cotton and textile goods made using Indian cotton. These goods are produced using raw materials and machines by perfectly competitive final goods producers with the production function $y_i = \left(\frac{1}{1-\alpha}\right)\left(\int_0^{N_i} x_i(k)^{1-\alpha} dk\right) Z_i^{\alpha}$, where y_i is output of textile goods of type $i \in$ (US, INDIA), $x_i(k)$ is the quantity of machine variety k used, N_i is the measure of machine designs of type i available, and Z_i is the quantity of raw materials. For this study, the relevant raw materials are cotton from the U.S. and cotton from India, each of which is used to produce the corresponding final good. I denote the price of raw materials from location i as c_i. The set of machine designs available for producing each type of output, N_i, represents the level of technology available for producers of the type i good. Both machines and raw materials are specific to the good that they are used to produce and production exhibits constant returns to scale when N_i is fixed. Machines fully depreciate after use.

The most important elements of the model are the machines and their makers. Machine making firms can invest in producing a new machine design. They then hold an infinite patent on this machine design, which allows them to produce and sell machines of that type. Once they have a design, machine makers produce machines of that type subject to a fixed marginal cost and then sell them at the monopoly price to final goods producers. The key to the model is the entry decision of new machine making firms. To enter, they must pay a fixed cost to generate a new machine design. Whether they pay this cost to expand the set of available technologies depends on the discounted present value of the new machine design, which in turn depends on the demand for machines from final goods producers.

In steady state, the discounted present value of producing a design for a machine of type i is $V_i = \beta p_i^{1/\alpha} Z_i / r$ where p_i is the price of final good and r is the interest rate. This equation shows the two key effects at work in the model. The direct positive impact of the quantity of raw materials of type i on the value of designs for type i machines, represented by Z_i in this equation, is called the *market size effect*. There is also a *price effect*, represented by p_i, that describes a negative relationship between the price of the final good of type i and the value of designs for type i machines. An increase in Z_i will increase the quantity of good y_i on the market and decrease p_i. Thus, the price effect channel will generate a negative relationship between the quantity of inputs Z_i and the value of machine designs of type i. Thus, the price and market size effects will work against each other to determine the overall relationship between the quantity of input i and the returns to innovation in machines using that input. The strength of the price effect depends on the extent to which an increase in Z_i reduces p_i. Define σ to be the (derived) elasticity of substitution between inputs, which depends on the elasticity of substitution between final goods and the production function parameter α. The value of σ determines the extent to which an increase in Z_i reduces p_i, and thus the strength of the price effect relative to the market size effect.

Holding technology fixed, an increase in the relative supply of an input results in a decrease in the relative price of that input. When technology can adjust, the model makes three main predictions:

Prediction 1: Relative technology (N_{INDIA}/N_{US}) is increasing in relative expenditures ($c_{INDIA}Z_{INDIA}/c_{US}Z_{US}$) on the balanced growth path.

Prediction 2: If $\sigma > 1$, an increase in relative input quantity (Z_{INDIA}/Z_{US}) will cause an increase in relative technology (N_{INDIA}/N_{US}) on the balanced growth path.

Prediction 3 (strong induced bias): If $\sigma > 2$, an increase in relative input quantity (Z_{INDIA}/Z_{US}) will cause an increase in the relative price of Indian cotton (c_{INDIA}/c_{US}) on the balanced growth path.

There is some evidence that the relevant elasticity of substitution for this study is greater than one, and potentially above two, but the available estimates are not reliable and precise enough to provide a structural test of the theory. The main challenge in estimating σ is the need to use annual data, which leaves us with relatively few observations to work with. Existing work by Irwin (2003) finds an elasticity of substitution between Indian and U.S. cotton of 1.96, but his approach imposes strong assumptions.[4] I have attempted to generate alternative estimates under weaker assumptions using weather shocks as instruments for relative supply. These results (available in Appendix A.5) suggest a higher elasticity of substitution (above 5.5), but with few observations the IV estimates are imprecise.

[4]Specifically, he uses an Almost Ideal Demand System approach that assumes that export supply is perfectly elastic, which will bias his results downward.

3 Empirical setting

3.1 Cotton textile production

In the second half of the 19th century, the cotton textile industry was the largest manufacturing sector in the world's leading industrialized economy. Cotton textiles were Britain's largest export and raw cotton was Britain's largest import.[5] In terms of employment, the 1861 Census of Population shows 456,646 people in England and Wales worked in cotton textile manufacturing, equal to 2.3% of the total population or 9.5% of manufacturing employment. The focus of this study is on effects occuring within the cotton textile industry, so to keep things simple I do not discuss impacts of the Civil War outside of this industry unless it is necessary for the analysis.[6]

Figure 1 describes the production process for cotton textiles, which can be divided into three stages: Preparation, Spinning, and Weaving/Finishing. The middle row of the figure describes some of the key machines in each production stage, while the bottom row indicates where each process was usually carried out. Preparation, the most important stage for this paper, involved separating the cotton fibers from the seeds using gins, opening the cotton fibers using openers, and cleaning the cotton by removing leaves, dirt, and other matter using scutchers and carding machines.[7] Ginning generally took place in the cotton producing region, while later stages, such as opening and carding, took place in spinning mills in manufacturing centers such as Britain. In the spinning stage, the prepared raw cotton was spun into yarn. The yarn was then made into fabric, through weaving, after which the fabric could be finished through bleaching, dying, or printing.

All of these production stages relied heavily on machinery which was supplied by Britain's large and innovative textile machinery sector. Technologically, this was a fast-moving sector. Textile innovations made up over 11% of British patents from 1855-1883. Historians document numerous instances of cotton textile technologies responding to changes in the market within a 1-2 year period, a figure that is consistent with the innovation lag documented in this study.[8]

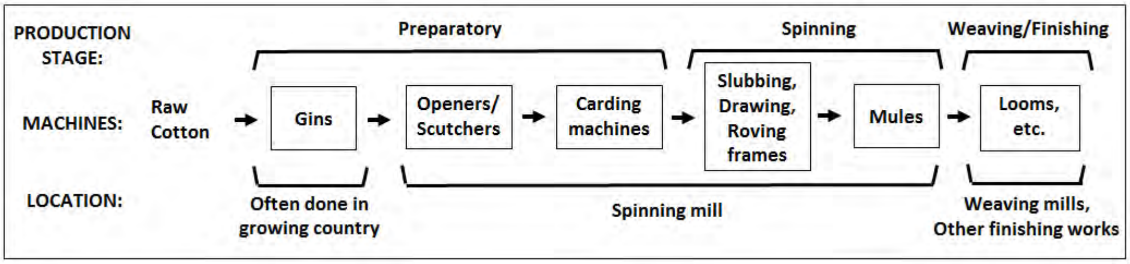
[5] Of course, this was not the case during the U.S. Civil War.

[6] Hanlon (2013) explores some of the impacts of the Civil War on other industries in Britain.

[7] Definitions of these and other textile-related terms are available in Appendix A.1.4.

[8] For example, in her authoritative history of the development of the cotton gin, Lakwete (2003) details numerous instances in which inventors produced new innovations or patentable improvements

Figure 1: The cotton textile production process



3.2 Sources of supply

The British cotton textile industry depended entirely on imported raw cotton supplies, since growing cotton was infeasible in Britain. Just prior to the U.S. Civil War, roughly three-quarters of these supplies came from the Southern U.S. (77% in 1860). The other major supplier was India, which supplied 17% of imports in 1860. The remainder came from smaller suppliers, including Brazil and Egypt (both around 3% in 1860).

This focus of this study is on cotton from the two main suppliers, the U.S. and India. This focus is consistent with the assessment of most contemporary observers, both before, during, and after the Civil War, who viewed India as the only viable alternative to American supplies. In 1859, *The Economist*, a leading commercial publication in the cotton districts, stated that, "practically speaking, we possess but two sources of supply...the United States and British India." This view was reiterated in an 1862 article titled "How is Cotton to be Got?" in which they write, "And at the outset, and to clear our ground, we may observe that India and America are

on existing inventions within a 1-3 year period. Among these inventors is Eli Whitney, who had invented, patented, and introduced commercially his famous cotton gin within two years of first setting foot on a Southern cotton plantation. Two other good examples are Macarthy's roller gin and Whipple's cylinder gin, which were both invented in response to the panic of 1837 and patented in the U.S. in 1840. These examples suggest that, at least in the case of gins, it is reasonable to expect innovation to respond to changing conditions within a one to three year time frame. Another piece of evidence from the same time period, though a very different industry, comes from Lampe & Moser (forthcoming). They find evidence that the introduction of a patent pool in the sewing machine industry led to an increase in patents of substitute inventions that spiked 1-3 years after the pool began.

practically the only two quarters which need occupy our attention..."[9] A similar view is offered in a retrospective piece on the efforts of the Cotton Supply Association, a group dedicated to encouraging new sources of cotton supply, by Isaac Watts (1871). In describing the failure of the Association to generate sufficient supplies from other locations to replace the shortage of U.S. cotton, he highlights that, while many countries possessed the climate to grow cotton, the availability of labor was the key missing ingredient in most countries. However, "one of the few countries in which this great barrier to progress is but little known is India."

One consequence of the predominance of the two main varieties was that innovators focused their efforts on technologies related to either U.S. or Indian cotton. Thus, when investigating technological change I concentrate my analysis on technologies related to these two varieties. However, the existence of smaller suppliers such as Brazil and Egypt is still helpful. While too small to be the focus of innovators, these varieties did have quoted market prices. As a result, they can be used to construct counterfactual relative price series in the absence of substantial innovations biased in their favor.

In order to identify technologies that were biased toward either American or Indian cotton, it is necessary to understand the key differences between these varieties. Here is discuss the most important differences, while further details are available in Appendix A.1. Indian cotton was a low-quality variety that competed primarily with the low or middle grades of U.S. cotton, both of which were used to serve the large market for low to medium quality goods. The raw cotton supplied by the U.S. and India at the time of this study came from biologically distinct varieties.[10] The cotton available from India in the 1860s was widely considered to be inferior to U.S. cotton along several dimensions.

One difference between these varieties was that Indian cotton was more difficult to prepare for spinning. In particular, it was difficult to remove the seeds from the Indian cotton using the cotton gins that were available prior to 1861. This was a result of the unusually small size of the Indian cotton seeds, as well as their strong

[9]Later the article states, "Nor can the quantity furnished to us regularly from Brazil or Egypt be much increased, either immediately or ultimately, for reasons we have more than once explained."

[10]There had been some efforts to introduce U.S. cotton plants into India prior to the U.S. Civil War, but these were unsuccessful. During the war, there was a redoubling of effort and growers achieved some success in limited areas of India such as Dharwar. However, the vast majority of Indian cotton continued to come from native Indian plants.

bond to the cotton plant (Wheeler (1862)). The primary machine used to remove seeds in India was the Churka, a very simple and inexpensive but inefficient and often ineffective hand-operated machine. The main alternative, prior to 1860, was the saw gin, which had been developed for processing American cotton and was also used for ginning high-quality cotton from Brazil and Egypt. However, American saw gins tended to cut up the Indian cotton fibers, reducing their length, and therefore their usefulness. As a result, the saw gin proved ill suited for India. In addition to the difficulty in removing seeds, Indian cotton fibers were also tightly compressed for shipping, making them difficult to open, a process which was done using openers.[11]

The U.S. also had a better developed cotton growing and processing industry than India, which influenced the cleanliness of the cotton. Indian cotton had a difficult journey from the interior to the ports, and passed through the hands of multiple middle-men, who habitually added dirt, salt water, or other substances in order to increase the weight of the cotton.[12] Compounding this problem, Indian cotton plants were leafier, which resulted in additional material being mixed in during picking. As a result, the Indian cotton required more cleaning than American cotton, a process that was done using gins, scutchers, and carding machines.

Indian and U.S. cotton also differed in their fiber length. Most of the raw cotton coming from the U.S. was of a medium-length variety, which was easier to spin than the short-fiber cotton supplied by India. The fact that Indian cotton was shorter likely compounded the difficulties involved in preparing the fibers, since ill-suited machinery could significantly shorten the fiber length.

Of these differences, the most important bottleneck for the use of Indian cotton was the removal of seeds, dirt, and other matter without damaging the fibers. These steps were done by gins, openers/scutchers, and carding machines. Prior to the Civil War, these early stage machines were well adapted for the use of U.S. cotton, as well as other high-quality varieties, but were poorly suited for dealing with Indian cotton. Thus, my analysis focuses on how innovation in these machine types reacted as the relative importance of Indian cotton increased during the Civil War.

[11]Compression for shipping was done using hydraulic presses. This process had some negative effects on cotton quality, but was still worth it when shipping from India, which faced much greater shipping distances and costs than the United States, Brazil, or Egypt, particularly before the opening of the Suez Canal in 1869. Patents filed in India show an increase in innovation related to these hydraulic press machines during the Civil War.

[12]See, e.g., the description in Wheeler (1862) (p. 125-129) and Mackay (1853).

3.3 The impact of the U.S. Civil War

After the beginning of the U.S. Civil War in April of 1861 the North immediately declared a naval blockade of Southern ports. While initially ineffective, the blockade became increasingly disruptive to Southern commerce, including the export of raw cotton, as the war continued and the Union Navy expanded.[13] The resulting increase in transport costs and other disruptions caused by the war had a significant effect on British imports. Other suppliers, particularly India, but also Brazil and Egypt, substantially increased supplies in response to the shortage of U.S. cotton. Yet they were not able to increase their production rapidly enough to replace the flows from the U.S. This pattern is visible in the left-hand panel of Figure 2. The right-hand panel of Figure 2 shows that there was a significant drop in British domestic cotton consumption from 1861-1865, a good indicator of production in the industry.[14]

Figure 3 shows the impact on the share of total import quantity from the U.S., India, and other suppliers (left panel), and the value of imports from each location (right panel).[15] It is clear that the shock caused a sharp drop in the import share of U.S. cotton and an increase in the share of imports from India and other suppliers. While imports from the U.S. dropped sharply during the war, significant supplies remained on the market, allowing me to obtain reliable price data for U.S. cotton throughout the shock period.[16] Overall expenditure on cotton inputs shifted toward Indian cotton, as shown in the right-hand panel of Figure 3.

[13] A graph showing transport costs during the early part of the Civil War is available in Appendix A.1.1. In addition to the Northern blockade, there were also efforts by the Confederate government to restrict cotton exports at the Southern ports in an effort to force Britain to intervene in the war.

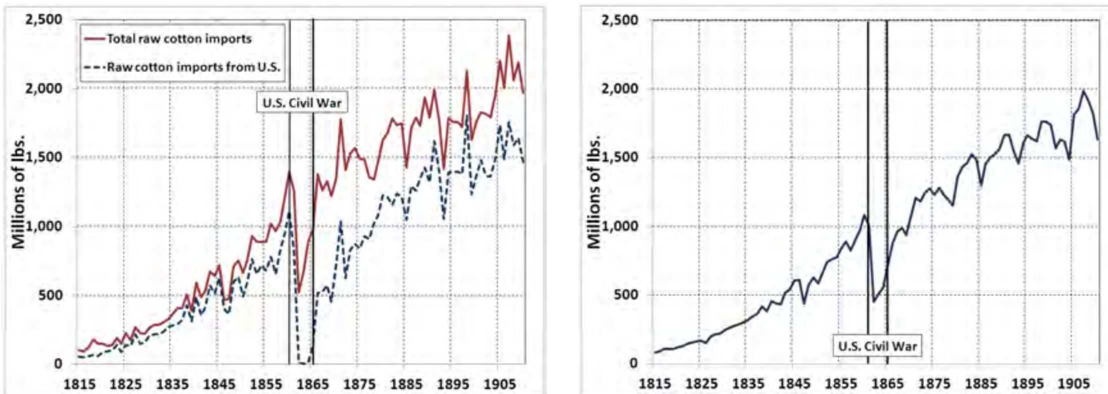
[14] The fall in production led to massive unemployment in the cotton textile districts, resulting in the "Lancashire Cotton Famine." Brady (1963) argues that in fact the drop in production was driven by an oversupply of cotton textile goods on the market in 1860-1861, rather than a drop in the availability of inputs. His argument is based on the fact that the ratio of cotton stocks to imports remained high during the war. However, when one considers the size of the reduction in imports and the drawdown in stocks over the 1861-1865 period, rather than comparing ratios, it is clear that his argument cannot be correct.

[15] Note that the import data shown in Figure 2 and 3 come from two different sources. The Mitchell & Deane (1962) data used in Figure 2 provide the longest time coverage but do not distinguish between imports from different sources.

[16] Imports from the U.S. never drop below 70,000 bales per year. For comparison, there were only 100,000 bales of Brazilian cotton imports in 1861. See Appendix A.1.2 for more details.

Figure 2: British cotton imports and domestic consumption 1815-1910

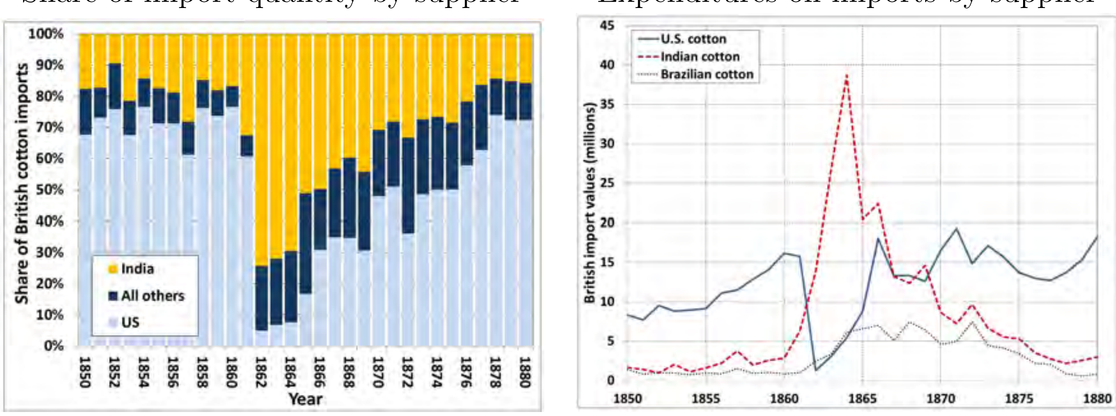
British cotton imports | British domestic cotton consumption



Data from Mitchell & Deane (1962).

Figure 3: British cotton import shares and expenditures, by supplier, 1850-1880

Share of import quantity by supplier | Expenditures on imports by supplier



Data from Ellison (1886).

These figures make it clear that the war caused large changes during the 1861-1865 period. Following the end of the war, conditions began returning to their original equilibrium. The overall level of imports and production rebounded almost immediately, but the re-adjustment of relative input supplies took time. Imports of American cotton remained low through 1870, while imports of Indian, Brazilian, and Egyptian cotton remained high through the mid 1870s. Also, while the share of Indian cotton in British imports falls back to pre-war levels by the late 1870s, overall Indian exports remained high through the 1870s, at least until the drought and famine of 1876-78, because of a diversion of Indian exports to the Continent following the opening of the Suez Canal in 1869.[17]

The expectations of British producers played an important role in their response to the onset of the war. The most important part of this calculation was agents' expectations about the potential end of slavery and how it would affect the productive capacity of the U.S. South. Many believed that the U.S. could not maintain the production levels achieved in the 1850s without slavery. By 1862 we observe reports suggesting that at least some believed that the war, though temporary, would cause a long-term shift in relative supplies.[18] It is therefore reasonable to think of the war as shifting, for at least some time, agents' expectations of the long-run growth path of the economy. This shift played an important role in innovation investment decisions.

4 Data

Most of the data used in this study was collected from original source material. In this section, I briefly describe how each of the main data sets were constructed, beginning with the patent data. Further details are available in Appendix A.2.

Patent data, while imperfect, are often the best available measure of innovation patterns and are widely used. The patent data used in this study are drawn from a large new set of British patent data which I have collected from around 1,500 pages of original printed documents. The novel feature of these data is that each patent is classified into one or more of 146 technology categories by the British Patent Office (BPO).[19] These classifications allow me to identify the type of technology underlying each patent. They also contain other useful information, including the patent title

[17]See figure 22 in the Appendix.

[18]To cite one example, The Economist (August 23, 1862) writes, "We admit, further, that, however and whenever this wretched and ruinous war may terminate, the ordinary routine of agricultural labor and the ordinary channels of transmission will have been so grievously disturbed that, for some time to come and perhaps for ever, the production of cotton in the Southern States will be smaller and costlier than it has been..."

[19]The purpose of this categorization was to aid inventors in identifying previously patented technologies.

and the name of the inventor. The analysis is conducted on data for 1855-1876, a period in which no significant changes to British patent law occurred. The dates given in the data represent the date of the patent application, rather than the date at which the patent was ultimately granted. Thus, the data identify patents at the earliest stage of the patenting process and we can dismiss concerns regarding delays in the granting of patents in the analysis.

This paper focuses on patents falling into the BPO's "Preparation & Spinning" technology category, which includes technologies used in the preparation of raw cotton, such as cotton gins and carding machines, as well as machines used in the spinning process, such as mules, yarn types, and other related technologies. Within the BPO "Preparation & Spinning" technology category, patents are listed in various technology subcategories which represent specific types of textile machinery. In the main analysis, I include the three "Preparation & Spinning" technologies that were most relevant for Indian cotton as well as any other technology subcategory that was important enough to receive at least one patent in each of the years from 1855-1876.[20] I also exclude four technologies which were not applicable to the use of cotton, since my focus is on changes occurring within the cotton textile industry.[21]

Three of these subcategories – Gins, Openers/Scutchers, and Carding machines – represented the primary bottleneck in the use of Indian cotton. To learn more about these machines, I reviewed hundreds of abstracts describing each patented technology.[22] This review allowed me to better identify patents related to Indian cotton. Within the "Openers/scutchers" subcategory, I further divide the patents into those machines applicable for cotton, which I label"Openers/scutchers – for cotton," and those machines focused instead on other inputs (e.g., flax, rags, etc.), which I label "Openers/scutchers – other". Within the Carding technology subcategory, the relevant technologies for using Indian cotton are those related to removing dirt and

[20]The subcategories used in the analysis are described in Table 4 in the Appendix. Confining the analysis to subcategories with at least one patent in each year ensures that the control technologies represent substantially important technology categories. Also, from a practical perspective this allows me to avoid some issues related to the presence of zeros in the data when analyzing the time-path of patents. I also provide robustness results that include a number of smaller technology subcategories.

[21]Most of these excluded technology subcategories were related to the preparation of flax. In the appendix, I check the robustness of the main results to including these non-cotton technology subcategories.

[22]These abstracts function somewhat like abstracts for academic papers. They are generally one or a few paragraphs describing the new technology, and often include a diagram.

other debris from the fibers. The BPO classifications identify two sub-subcategories related to dirt removal. Thus, I divide the carding machine subcategory into "Carding – dirt removal" technologies, which are relevant for using Indian cotton, and the remainder, "Carding – other."

This leaves me with three technology series which were the most important for the use of Indian cotton: (1) Gins, (2) Openers/Scutchers – for cotton, and (3) Carding machines – dirt removal. In the main analysis I compare these to the 19 other large "Preparation & Spinning" technologies. Some addition Indian-related patents, having escaped my review, may remain outside of these three categories. These will act to bias my results against finding evidence of directed technical change towards Indian cotton.

Adjusting for quality is important when using patent data because raw patent counts mask the quality of the new technology represented by individual patents, which may vary widely. For this study, I collected new data providing two measures of patent quality. The first measure is based on the payment of patent renewal fees, which patent holders were required to pay at the end of the third and seventh years of the patent term in order to keep the patent in force.[23] Since just under 18% of patents were renewed at three years, the payment of these renewal fees represents a substantial investment which would only have been worth it for the most successful technologies.[24] The second quality measure is based on mentions of the patent in a contemporary periodical, *Newton's London Journal*.[25] This monthly journal, devoted to covering new patents and other technology-related topics, was published by William Newton & Sons, one of the preeminent London patent agents.

In addition to the patent data, I draw on two sources of additional evidence reflecting technical change. One source of data comes from the surviving records of one of the leading machine producers at the time, Dobson & Barlow of Bolton. These data were gathered from original hand-written order books, available in the Lancashire Archives. They describe the number of gins ordered during the Civil War

[23]Renewal fee data have been used as an indicator of patent quality in previous studies (Pakes (1986), Schankerman & Pakes (1986), Lanjouw *et al.* (1998)), including some using historical British patent data (Sullivan (1994), Brunt *et al.* (2012)).

[24]Because so few observations of patents renewed at year seven are available, I use only the renewals filed at year three.

[25]Contemporary periodicals have previously been used to value historical British patents by Nuvolari & Tartari (2011).

period, and more importantly, they specify the type of gin ordered. Thus, they allow me to track the evolution of the designs of gins produced.[26] A second source is based on data from Forwood (1870) showing the percentage of cotton wasted in aggregate British production. The amount of waste is calculated by taking the total weight of raw cotton consumed by British mills in a year and subtracting the weight of yarn they produced. These data provide insight into the impact of new technologies on one important aspect of industry productivity.

Finally, I look at the impact of these machines on market outcomes using new price data that I gathered from market reports printed in *The Economist* magazine. The data cover 1852-1875. While the data were collected on a monthly basis, I average by quarter to reduce short-term volatility and measurement error. These data are available for the following benchmark cotton varieties: Upland Middling and Upland Ordinary from the U.S., Surat Fair from India, Pernambuco Fair from Brazil, and Egyptian Fair. Of the two U.S. varieties, the Upland Middling was a higher quality variety that was more comparable to the high-quality cotton from Brazil and Egypt, while the Upland Ordinary was a lower-quality variety that was more comparable to Indian cotton. Thus, I generally compare Indian cotton prices to those of Upland Ordinary, the most comparable U.S. price series.

A key feature of the price data is that they are for specific quality grades. Quality grading was a serious business at this time, undertaken by trained professionals. Quality changes that might occur as a result of the introduction of new techniques in the producer country would be reflected in shifts across the quality bins, with only a limited scope for quality changes within a grade. As a result, the prices we observe can be thought of as representing a fixed quality level.

5 Empirical analysis

The empirical analysis begins by using patent data to uncover the innovation response to the change in relative input supplies. These innovation patterns are then tied to investments in new or improved machinery using machine production data. Data on

[26]Similar order data are available for other machine types, including carding machines and openers/scutchers, but it is not possible to track the pattern of technological progress in these orders because new technologies were embedded as parts in larger machines, rather than completely different machine types.

the waste generated in the production process are used to calculate the impact of these new technologies on one aspect of aggregate productivity. Finally, price data are used to investigate the impact on overall market outcomes.

5.1 The direction of innovation

To investigate the direction of the technical change, I use data on patents in 22 technology subcategories within the BPO Preparatory & Spinning technology category. Patents of technologies in the Preparatory & Spinning technology category show a substantial increase during the Civil War period. In contrast, patents in the other major textile-related technology category, Weaving & Finishing, do not increase, nor do patents across all other technology categories.[27] This motivates my focus on these early-stage textile technologies.

The left-hand panel of Figure 4 graphs the count of patents in the three technology types that were most important for using Indian cotton and the average count of patents in the other 19 Preparatory & Spinning technology subcategories. We can see that all three of the crucial technologies for using Indian cotton experienced a sharp increase during the Civil War period, while other technologies show no positive response.[28] The right-hand panel of the figure describes the ratio of patents of technologies related to Indian cotton to all other subcategory patents. Prior to the war, the technologies important for using Indian cotton made up only around 4-6% of subcategory patents. This ratio rose above 15% during the 1861-1865 period, with the peak in 1863, but had fallen back to 6% by 1867.

The results in Figure 4 provide evidence of directed technical change towards technologies that augment Indian cotton. In the context of the theory, this would mean an increase in N_{INDIA}/N_{US}, and given that we have observed an increase in expenditures on Indian cotton relative to U.S. cotton during this period, this is consistent with the predictions of the theory. These results also foreshadow the differences-in-differences approach taken in the econometric analysis.

Note that the timing of these patterns differs across gins, openers/scutchers, and

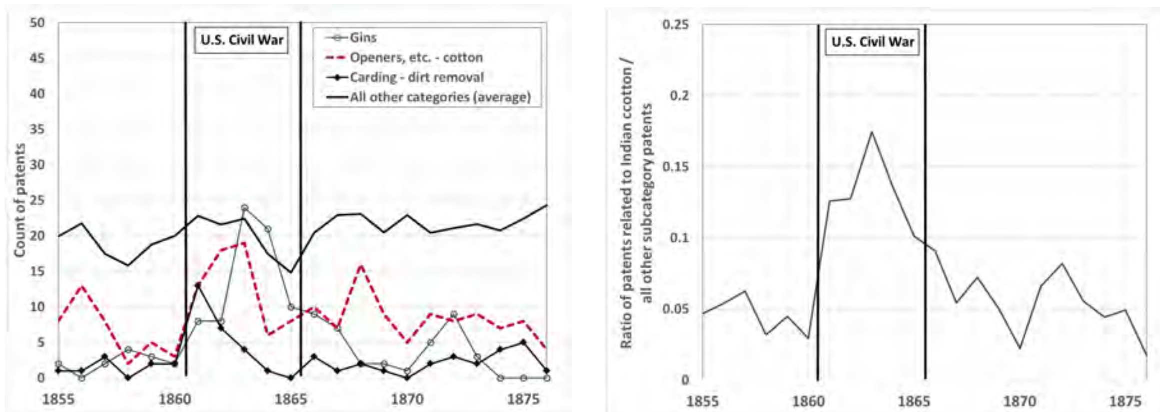
[27] See Figure 23 in Appendix A.3. The reason that we see no effect on Weaving & Finishing technologies is that this category includes only machines used in the later stages of the production process. By the time the cotton reached these later stages, either the major quality issues had been dealt with or the cotton had been rejected as waste.

[28] Graphs showing patent counts for all subcategories are available in the Appendix.

Figure 4: Comparing Indian-related patents to other Preparatory & Spinning patents

Count of patents

Ratio of Indian-related to other subcategories



These panels use data from 22 technology subcategories within the Preparatory & Spinning technology category. The three categories related to Indian cotton are Gins, Openers/scutchers – for cotton, and Carding technologies – for dirt removal.

carding machines. The increase occurs earliest in patents for carding machines related to dirt removal, while patents for openers/scutchers peak in 1862-63 and gins don't reach a peak until 1863-1864. A review of the historical record, and the patents themselves, offers two explanations for this pattern. The first has to do with the nature of the technologies being invented. Gin patents often represented entirely new machines, and sometimes entirely new ginning concepts. In contrast, many of the patents in the openers/scutchers and carding categories were modifications of parts of machines or adjustments to otherwise well-developed production systems. Many of these carding and opener/scutcher technologies could be adopted quickly by modifying existing machines; as an example, the Dobson & Barlow data show that the firm received 53 orders to alter existing carding machines during the U.S. Civil War, covering at least 1,085 individual machines.[29] Thus, technological complexity helps explain why innovations in carding machines and openers/scutchers appeared so rapidly, while there was a longer lag before the peak of innovation in gins.

A second explanation for the timing patterns in Figure 4 is that British machine

[29]Pre-war data, available only for Nov. 1860 - March 1861, show zero orders for the alteration of carding machines, suggesting that this surge in alterations was driven by the Civil War.

producers had less experience in producing gins, and in creating new gin designs, than they had for openers/scutchers or carding machines. Carding machines, openers, and scutchers were an important part of the output of diversified textile machinery firms. In contrast, prior to the Civil War most American cotton was ginned using American-made gins, while Indian cotton was ginned using crude locally produced equipment. This left little room for British engineering firms to produce gins. This is illustrated in the Dobson & Barlow production data, which shows no evidence that that firm produced gins prior to the Civil War. Thus, British producers had more to learn about gin production and design than about other technology types.

Next, I analyze these patterns econometrically using a panel data approach. The primary data set spans 22 years (1855-1876) and 22 technology groups, three of which are related to Indian cotton. Analyzing these data econometrically requires that I deal with a number of issues, some of which are the subject of ongoing research and debate. One issue is truncation in the data, since some of the data series show zero patents in some years. This is a particular problem with the three technology types related to Indian cotton, since there was little interest in these types of technologies in the pre-war period. A second issue is serial correlation, which Bertrand *et al.* (2004) have shown can generate substantial bias in panel data regressions. A third issue is that I am conducting panel data analysis with a small number of cross-sectional units.

To deal with these issues, I begin by aggregating the data into pre-shock, shock, and post-shock periods.[30] One advantage of aggregation is that it avoids the need for

[30]This follows the suggestion by Bertrand *et al.* (2004), who show that aggregation can help deal with serial correlation issues and performs well in small samples. Aggregating appears to be an effective solution to serial correlation issues in my data. Applying the panel-data serial correlation test from Wooldridge (2002) to the annual data with the three treatment groups pooled together as in Equation 1 yields a F-statistic of 8.148 and a p-value of 0.0095. After aggregation, the same test yields an F-statistic of 2.87 and a p-value of 0.1049. It is worth keeping in mind here that the small-sample properties of these tests are not well studied. There are two promising alternatives to aggregation for dealing with serial correlation. One is to cluster by technology category, allowing errors to be correlated over time, and then make a small-sample adjustment. A second alternative, which I apply later, is to exploit the time-series nature of the data and calculate Newey-West standard errors. The current literature does not provide clear guidance on which of these alternatives is preferred. My preference for aggregation is based on the fact that aggregation also eliminates zeros in the data, which allows me to run regressions in logs and avoid the use of count data models. The data show no evidence of substantial cross-sectional dependence, passing Pesaran's test for cross-sectional dependence in panel data with a p-value of 0.2835. See Hoyos & Sarafidis (2006) for a discussion of the test.

count data models, which are often required when using patent data, and eliminates all zeros in the data. At the same time, it addresses serial correlation issues. However, aggregating this way also reduces the available data, making it less likely that I find statistically significant results.

After collapsing the data for each subcategory into pre-shock, shock, and post shock periods, the regressions specification is,

$$\log(PAT_{jt}) = \alpha + \beta\,(S_t \times INDIATECH_j) + \Psi_j + \xi_t + e_{jt}, \tag{1}$$

where PAT_{jt} is the average count of patents in subcategory j and period t, Ψ_j is a full set of subcategory-specific fixed effects, ξ_t is a set of year indicator variables, and e_{jt} is an error term. The key explanatory variable is the interaction between an indicator variable for the shock period, S_t, and an indicator variable, $INDIATECH_j$, for the "gins", "openers/scutchers applicable to cotton", and "carding machines for dirt removal" subcategories.

The regression results are displayed in Table 1. Column 1 presents results including the pre-shock, shock, and post-shock periods, while Column 2 presents a more standard differences-in-differences approach with only the pre-shock and shock periods. Robust standard errors are in parentheses. We can tell from the standard errors in Table 1 that the coefficients are statistically significant under standard inference procedures based on asymptotic results.

Conducting inference using standard approaches may lead to underestimated confidence intervals in this setting because of the small number of panels (22) in the data.[31] To address this concern, I present the results of two small-sample corrections. In the single brackets I offer p-values from a permutation-based approach where I take every permutation of three technology groups, out of the 22 groups in the analysis, and treat them as if they were the treated technologies. This generates 22 choose 3 = 1540 coefficient estimates. Under the null hypothesis of no effect, these coefficients will have the same distribution as the estimated coefficient from Equation

[31] A number of approaches have been offered for dealing with this issue. These include bias corrections (MacKinnon & White (1985), Bell & McCaffrey (2002)), bootstrap-based approaches (Cameron *et al.* (2008)), the use of t-distributions for inference (Donald & Lang (2007), Imbens & Kolesar (2012)), and using permutations reassigning treatment to control groups to estimate the distribution of the test statistic (Conley & Taber (2011), Ibragimov & Muller (2010)). I have explored a variety of alternatives to the approach presented and they all confirm the pattern documented here.

1. Thus, they can be used for inference with exact size.[32] Alternatively, I follow the advice of Imbens & Kolesar (2012) by calculating heteroskedasticity-robust HC2 standard errors (MacKinnon & White (1985)) and then conducting inference using a t-distribution with a data-determined degrees of freedom based on the formula from Welch (1947).[33] The p-values obtained from this procedure are presented in double brackets. It may seem somewhat surprising here that the permutation based approach delivers results which are much stronger than those from the Imbens & Kolesar (2012) approach. The cause of this is not the HC2 standard errors. The difference comes almost entirely from conducting inference with a t-distribution with very few degrees of freedom. This is a very conservative distribution, with confidence intervals more than twice as wide as under normal standard errors. Thus, the p-values in double brackets should be viewed as very conservative.

Table 1: Response of technologies related to Indian cotton during the Civil War

	Dependent variable: Log Patents	
	Comparing shock period to pre and post-periods	Comparing shock to pre-period only
India-related x Shock period	1.127	1.254
	(0.276)	(0.302)
	[0.000]	[0.000]
	[[0.044]]	[[0.049]]
Subcategory effects	Yes	Yes
Time period effects	Yes	Yes
Observations	66	44
Number of panels	22	22

The pre-shock, shock, and post-shock periods which are, respectively, 1855-1860, 1861-1865, and 1866-1876. **Parentheses** contain robust standard errors. **Single brackets** contain p-values from a permutation-based approach in which I select every permutation of three technologies out of the 22 technology categories (22 choose 3 = 1540) and estimate the impact on these three during the shock period. The distribution of these "placebo" coefficients is then used to construct the p-value of the treatment coefficient. Histograms of these coefficients are available in Appendix A.3. **Double brackets** contain p-values from a test based on HC2 standard errors tested against a t-distribution with a degrees of freedom determined using Welch's (1947) formula. For the specification in Column 1, Welch's approach gives a degrees of freedom of 2.35. For the specification in Column 2, Welch's formula gives 2.55.

[32]This approach has been used by Bloom *et al.* (2013) and is similar to the approach suggested by Conley & Taber (2011). Histograms of the estimated permutation coefficients are available in Appendix A.3.

[33]Imbens & Kolesar (2012) suggest using a data-determined degrees of freedom based on the Bell & McCaffrey (2002) but that approach requires an assumption of homoskedasticity that does not appear to be a good fit for my data. Nevertheless, the two approaches deliver very similar results.

These results confirm the patterns from Figure 4: there was a substantial increase in patents related to Indian cotton during the Civil War period, relative to all other types of Preparatory & Spinning technologies. These patterns are statistically significant even under a very conservative approach. Further results, available in Appendix A.3, show that these findings are robust to variation in the underlying data, such as the inclusion of small technology subcategories or considering only patents with "cotton" in the title.[34]

One feature of the approach taken above is that it does not allow me to explore the pattern of these effects over time. Investigating the timing of these impacts in more detail requires that I use annual data and a slightly different econometric approach. I begin by summing patents from the three treated categories into one treated technology category, called $INDIATECH2_j$, which eliminates all zeros in the data. I then run the following regression specification,

$$\log(PAT_{jt}) = \alpha \quad + \quad \left[\sum_{k=1858}^{1876} \beta_k \times YR_k \times INDIATECH2_j \right] + \Psi_j + \xi_t + \epsilon_{jt} \tag{2}$$

where YR_k is an indicator variable for year k. To assess pre-trends, I begin estimating coefficients several years before the onset of the conflict. To deal with heteroskedasticity and serial correlation I calculate Newey-West standard errors.[35] There is no evidence of time-trends in the series, so I do not include time-trends in the regression.[36]

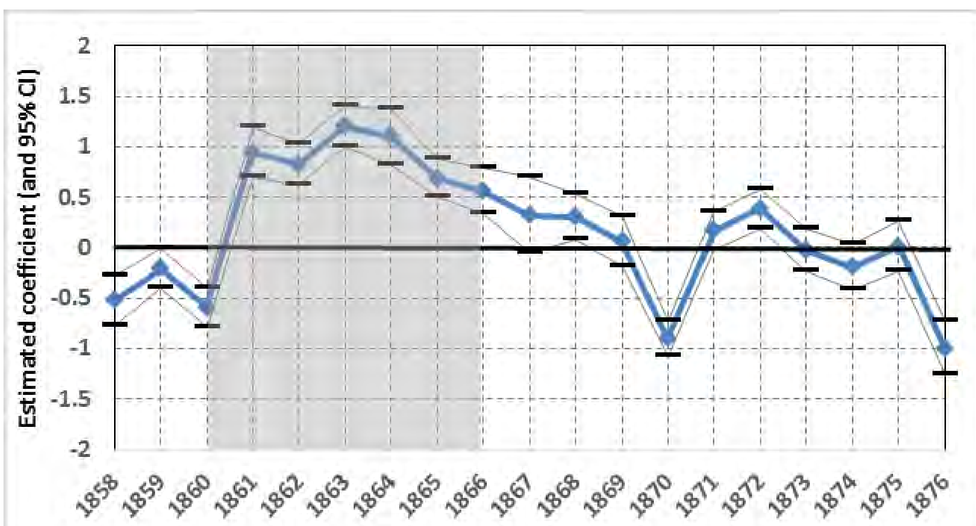
[34] There is also evidence that all three Indian-related technology categories experienced significant increases during the Civil War period. Results are presented in Appendix A.3 Table 7. However, for reasons discussed in that Appendix, the small-sample corrections do not perform well in that specification, so those results must be interpreted with caution.

[35] Hansen (2007) shows that HAC estimators of this type provide valid inference either as N and T go to infinity jointly, or as T goes to infinity with N held fixed. His Monte Carlo simulations also suggest that these estimators perform well in samples comparable in size to mine. In the appendix, I explore two alternative approaches to generating the confidence intervals. The first uses clustered standard errors while the second follows Angrist & Lavy (2009) in using the Bias Reduced Linearization approach introduced by Bell & McCaffrey (2002). These approaches generate similar results.

[36] Because of the relatively short and volatile pre-period, results generated with time-trends are highly sensitive to the number of pre-periods included in the summation in Equation 2. This feature, plus the lack of clear time-trend in the data, suggests that including time-trends in the regressions is likely to reduce the accuracy of the estimated results.

The results are presented in Figure 5. There is no evidence of an increase in Indian-related technology patents prior to 1861, and in fact patents in these categories were unusually low, perhaps due to the disruptions in Indian cotton supplies following the Indian Rebellion of 1857-58. This is consistent with the historical record, which indicates that people were surprised by the magnitude of the conflict. Starting in 1861, patents in categories related to Indian cotton increased substantially, peaking in 1863, and declining thereafter. There is some evidence that the high level of patents in these categories extended beyond the end of the war to 1867. This pattern is consistent with some path dependence in innovation, such as that hypothesized by Acemoglu *et al.* (2012), and may also lead to a slight downward bias in the results presented in Table 1.

Figure 5: Pattern of patents related to Indian cotton over time



This chart shows estimated coefficients and 95% confidence intervals for the interaction between technologies related to Indian cotton and each year from 1858-1876. The dependent variable is the log of patents in each subcategory-year. The Indian-cotton-related technology category is formed by aggregating the Gins, Openers for Cotton, and Carding for Dirt Removal technology categories. Thus, the data include 20 technology categories over 22 years (1855-1876) with one treated category. Confidence intervals are based on Newey-West standard errors with a lag length of 3 (based on Greene's rule-of-thumb lag length of $T^{1/4}$ rounded upwards).

When using patent data, it is always important to account for the quality of inventions, which may be obscured when only raw patent counts are used. To investigate the behavior of high-quality patents during the Civil War, I use the approach from Equation 1, but with the count of high-quality patents PAT_{jt}^{H} used in place of the count of all patents PAT_{jt} in a technology and period.

To identify high-quality patents I use two approaches. First, I look at those patents for which the renewal fee was paid at year three to keep the patent in force. Renewal fee data is available for 1856-1869, so I can compare pre-shock, shock, and post-shock periods. The second quality measure is based on abstracts included in a contemporary periodical, *Newton's London Journal*. Those data are available from 1854-1864, so I compare the pre-shock period to the shock period. Graphs of both series are available in Appendix A.3.2.

Results are presented in Table 2. There is evidence of an increase in high-quality patents related to the use of Indian cotton during the Civil War. These results are statistically significant under the permutation-based approach, but only marginally statistically significant under the more conservative Imbens & Kolesar (2012) approach. Graphs, available in the appendix, show that this increase in renewed patents was present even for patents which would have been renewed after the end of the Civil War.

Next, I turn to two non-patent measures of technological progress. The first is drawn from the order books of Dobson & Barlow, a textile machine producing firm. This was an important firm, employing 1,600 workers in 1860 and supplying a full line of textile-related machinery. The firm was also active in innovation, particularly in gins and carding machines. The firm produced no cotton gins in the pre-war period, but this changed dramatically starting in 1862, and gins made up an important part of overall machine sales during much of the Civil War period.[37]

These data allow us to observe the evolution of the different gin types that Dobson & Barlow produced over the Civil War period and compare this pattern to their gin patents. Figure 6 shows the share of gin orders made up of each of the four gin types produced by Dobson & Barlow from 1860-1866. The data show a rapid evolution, starting with Excelsior gins, moving to Macarthy gins, followed by the less-successful Improved Portable Hand Gin, and finally the Knife Roller Gin. At the bottom of the figure is a list of Dobson & Barlow patents of gin technology over the period.

[37] American cotton was generally ginned using American-made gins, while prior to the war Indian cotton was ginned using simple locally produced hand-gins. Thus, it is not surprising that Dobson & Barlow were not active in gin production in the pre-war period.

Excluding the first patent, which was for a driving apparatus, we can see that the patent applications tended to correspond to the introduction of new gin types.[38] The introduction of the Improved Portable Hand Gin in December of 1863 closely follows a patent filing in November of 1863. Similarly, two gin patents were filed in January of 1865 and the firm begins switching production to the new Knife Roller Gin soon after. These patterns suggest a close link between patenting and production.[39]

Table 2: High-quality patents related to Indian cotton during the Civil War

	Dependent variable: Log Patents		
	Patents paying renewal fee after three years		Patents mentioned in *Newton's London Journal*
	(1)	(2)	(3)
India-related x Shock period	1.343	1.805	0.887
	(0.482)	(0.554)	(0.475)
	[0.002]	[0.001]	[0.052]
	[[0.125]]	[[0.086]]	[[0.204]]
Subcategory effects	Yes	Yes	Yes
Time period effects	Yes	Yes	Yes
Included time periods:	Pre-shock, shock post-shock	Pre-shock, shock	Pre-shock, shock
Observations	66	44	40
Number of panels	22	22	20

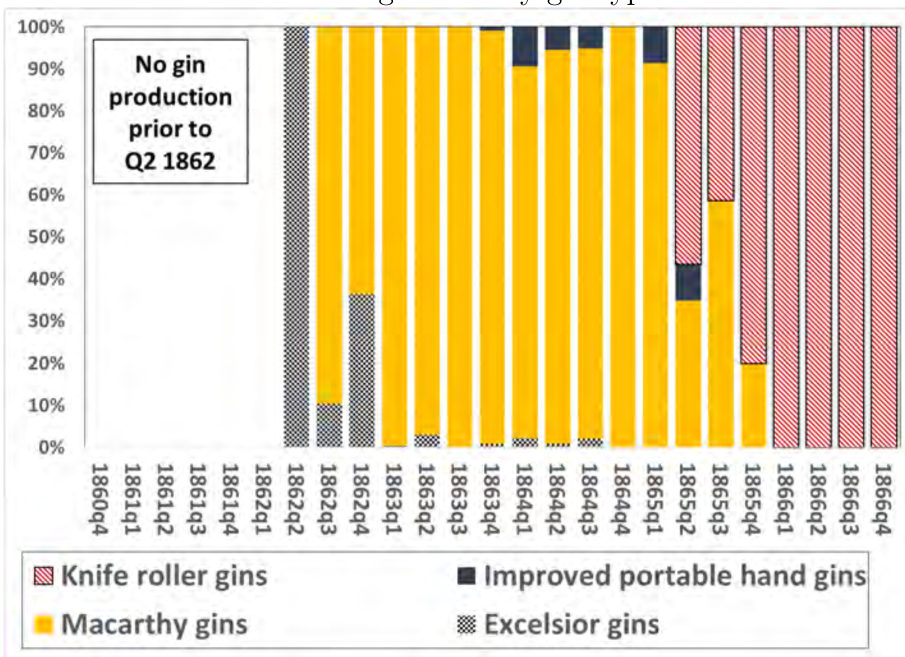
The renewal fee data used in columns 1-2 cover 1856-1869 and the shock period is 1861-1865. The data used in column 3 cover 1854-1864 and the shock period is 1861-1864. Patents are classified by the application date. The "Bobbins" and "Winding-on" technology subcategories are omitted from the data used in Column 3 because they have zero mentions in Newton's London Journal in at least one of the periods. **Parentheses** contain robust standard errors. **Single brackets** contain p-values from a permutation-based approach in which I select every permutation of three technologies out of the available technology categories and estimate the impact on these three during the shock period. The distribution of these "placebo" coefficients is then used to construct the p-value of the treatment coefficient. Histograms of these coefficients are available in Appendix A.3.2. **Double brackets** contain p-values from a test based on HC2 standard errors tested against a t-distribution with a degrees of freedom determined using Welch's (1947) formula. For the specification in Column 1, Welch's approach gives a degrees of freedom of 2.31 For Column 2 it gives 2.45. For Column 3, it gives 2.90.

[38]Note that a patent application granted provisional protection with the application date as the priority data. Thus, once a patent application is filed the patent applicant can begin using the patented technology.

[39]Because the patents are given as a set of technical specifications, and I do not have the technical specifications for the gins sold by Dobson & Barlow under each name, I cannot definitively link the patents to the new machines that were introduced.

Figure 6: Dobson & Barlow share of gin sales by type and gin patents

Share of gin sales by gin type



Gin patents

Year	Month	Patent No.	Applicant	Patent title
1862	Oct.	2765	Barlow, E	"Certain improvements in machinery for driving cotton gins and for preparing and combing cotton and other fibrous substances."
1863	Nov.	2915	Dobson, B & Barlow, E	"Machinery for ginning cotton and for opening cotton and other fibrous substances."
1865	Jan.	44	Dobson, B	"Machinery for ginning cotton."
1865	Jan.	248	Dobson, B	"Cotton gins."

Sales data from Dobson & Barlow contract books accessed at the Lancashire County Archives. Gin contracts were reviewed from October 1860 - December 1866. The date is based on when the contract was received. Patent titles from the *Cradle of Invention* database.

Next, I present evidence suggesting that these new technologies had an impact on aggregate productivity in cotton textile production. To do so, I focus on one important and observable element of productivity: the waste produced as part of the production process. The level of waste is simply the difference between the the weight of raw cotton consumed by spinning mills and the weight of yarn produced. Waste was generated in two primary ways. First, raw cotton going into the mills may be weighed down with dirt and other debris. When this is removed as part of the production process, it will show up as waste in these calculations. Second, cotton may be damaged during the preparatory process in the mills, making it useless for spinning. Improved preparatory stage technologies could thus reduce waste in two ways: by reducing the amount of materials contaminating the raw cotton entering the mills, or by reducing damage to the raw cotton done through the production process.

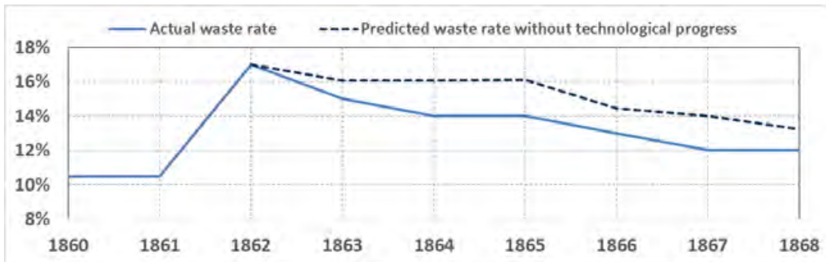
Data from Forwood (1870) describes the percentage of raw cotton wasted in the production process from 1860-1868. This waste percentage is shown in the solid line in Figure 7. The sharp increase in waste in 1862 is an indicator of the difficulties faced by British producers as they shifted toward using Indian cotton. This increase is particularly striking given that prices had increased substantially by 1862 (see next section) and producers must have been working to minimize wastage at that time.

To assess the impact of new machinery and techniques on cotton waste I conduct a simple calculation. Suppose that the increase in cotton waste from 1860 to 1862 is due to the increase in the share of Indian cotton consumed by British mills, which rose from 7% in 1860 to 59% in 1862.[40] This suggests a waste rate of 22% for Indian cotton compared to 9.6% for non-Indian (mostly American) cotton. If these percentages remained the same after 1862, then the overall waste share we would expect is given by the dotted line in Figure 7. This line is declining slowly due to the declining share of Indian cotton imports after 1862, but does not decline as fast as the actual waste share. The difference between the solid and dotted lines can be thought of as a rough estimate of the impact of improved technology on waste in the production process. This simple calculation suggests a fall in the waste generated from spinning with Indian cotton to 15.5-17.9% by 1866-1868, a 19-30% improvement over the original level.[41] These results are consistent with the timing of the introduction of new machines and suggest that these machines had a substantial impact on aggregate productivity.

[40] Note that the increase in consumption of Indian cotton was small in 1861, reaching just 15% of consumption, despite a larger increase in imports. This is most likely because the jump in imports occurred late in the year and producers put off using the less attractive Indian cotton as long as possible.

[41] The estimated waste share for non-Indian cotton for the 1866-1868 period ranges from 9.9-10.1%, suggesting that for cotton other than from India there was little improvement in the waste rate over that period.

Figure 7: Percentage of cotton wasted in production



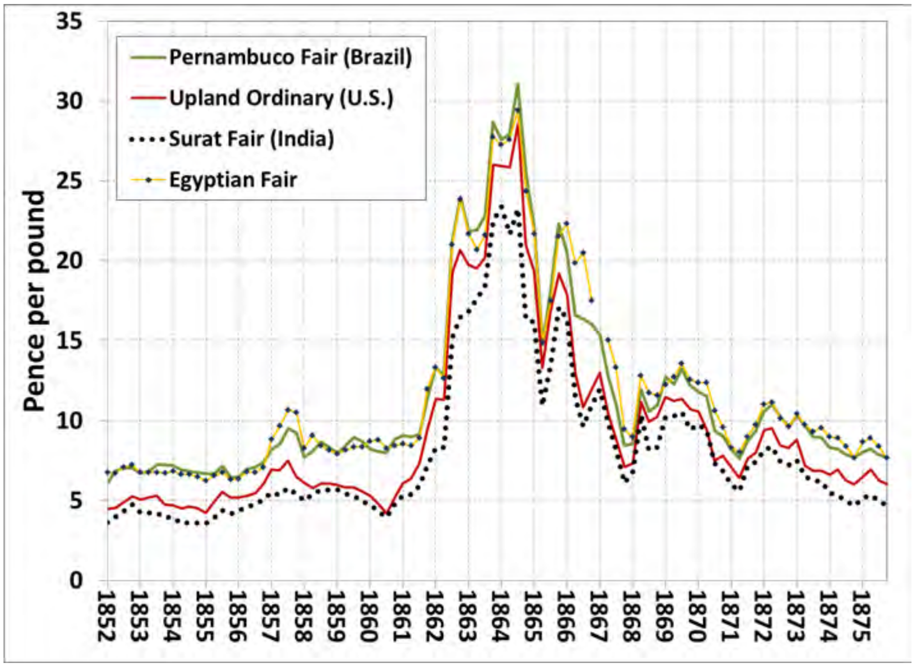
Solid line describes the actual percentage of raw cotton weight that is lost in the production process. **Dotted line** is constructed by comparing the increase in waste from 1860-1862 to the increase in the share of Indian cotton in cotton consumption by British mills over that period in order to calculate the percentage of waste rates for Indian and non-Indian cotton. Holding the waste rates constant, I then project aggregate waste shares for years after 1862 based on the share of Indian cotton in total consumption. Data from Forwood (1870). The predicted waste level for 1864 is interpolated because Forwood does not report cotton consumption data for that year.

5.2 Price responses: strong induced bias

This section explores the impact of the change in relative input supplies on relative input prices in the presence of directed technical change. Of particular interest is the strong induced-bias hypothesis: the idea that, if technical change is strongly biased towards an input that has become relatively more abundant, the relative price of that input can rebound, and may actually increase, despite the increase in relative supply.

Figure 8 plots the price data used in this analysis. I use prices for the two large varieties, U.S. and Indian cotton, as well as two smaller varieties, Brazilian (Pernambuco) and Egyptian cotton. In all periods, these prices are roughly ordered according to quality, with Brazilian and Egyptian fetching the highest prices, and Indian cotton the lowest. We can see that the onset of the Civil War was followed, with some lag, by a sharp increase in the price of all cotton varieties. Prices remained high through 1865 and began to decline in 1866.

Figure 8: Raw cotton prices on the Liverpool market for key varieties 1852-1875



Quarterly price data from *The Economist*. Upland Ordinary is the benchmark lower-quality U.S. cotton variety. Surat is the benchmark Indian cotton variety. Pernambuco is the benchmark Brazilian cotton variety.

What we cannot see in Figure 8 is the behavior of relative prices, which is our primary interest. In Figure 9, I graph the relative prices of Indian/U.S. cotton, Brazilian/U.S. cotton, and Egyptian/U.S. cotton for 1852-1875.[42] To make things easier to compare, I have put each relative price line in logs and set the average price in 1852 to equal one for each series. Prior to the war, we can see that the relative prices moved within a similar range, though they did not move together.[43] All of the relative prices fell sharply at the beginning of the war, following a fairly similar pattern through early 1862. However, during 1862 the relative price of Indian cotton began rising, while the price of the other alternative varieties continued to fall. More detailed monthly data, available in the appendix, allows me to pinpoint the beginning of the increase in the relative price of Indian cotton to October of 1862. The relative

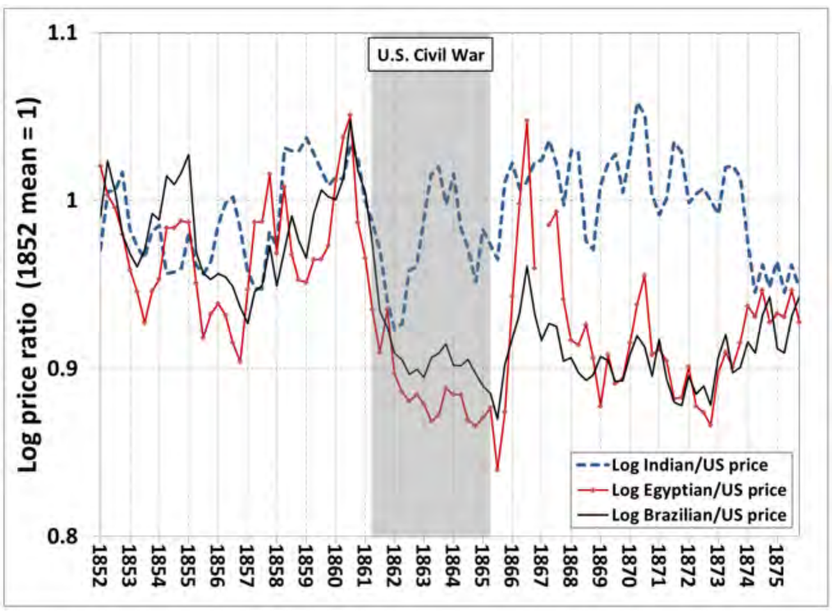
[42]Additional price graphs are available in Appendix A.4. I end the graph in 1875 because 1876 marked the beginning of the Great Indian Famine, which sharply reduced Indian cotton exports and marked the end of the period of relative abundance of Indian cotton.

[43]Given the importance of idiosyncratic shocks such as bad weather and crop diseases, this is not surprising.

price of Indian cotton peaked in 1863 and remained high through the early 1870s, before moving back in line with the other varieties in 1874.[44] In contrast, the relative prices of the alternative varieties remained low throughout the period in which they remained relatively more abundant.[45]

The rebound in the relative price of Indian cotton starting in late 1862 is consistent with the strong induced-bias hypothesis. This pattern occurred despite the fact that the share of imports made up of Indian cotton increased from 17% in 1860 to 34% in 1861, more than doubled to 74% in 1862, and then remained high through 1876. The timing of this rebound also fits the pattern of innovation well; by late 1862, many new technologies had entered the market, and others would follow soon after.

Figure 9: Comparing relative cotton price movements



Price data gathered from The Economist magazine.

[44]This may be because the technologies developed in the mid-1860s were no longer at the technology frontier by the mid-1870s. Given the rapid pace of technological advance in this industry during this period, such a pattern would not be surprising.

[45]The main exception to the pattern of low relative prices for Egyptian and Brazilian cotton is the increase in the relative price of Egyptian cotton in 1865-1867. This increase was the result of a sharp decrease in the quantity of Egyptian cotton on the market due to poor agricultural conditions. Data from Ellison (1886) shows a drop in British imports of cotton from the Mediterranean (largely made up of Egyptian cotton) from 413,890 bales in 1865 to 198,170 bales in 1867, followed by a slow rebound after 1867.

There is evidence in Figure 9 of a high relative price of Indian cotton in 1858, prior to the Civil War. This increase was due to the short-term effect of the Indian Rebellion of 1857, which caused a sharp short-term reduction in the availability of Indian cotton (from 680,500 bales in 1857 to 361,000 in 1858). This temporary reduction in supply had the expected positive effect on relative prices. It is interesting that the relative price of Indian cotton during this period of shortage is similar to that reached in the late Civil War period even though the quantity of Indian cotton on the market was much higher, reaching 1,866,610 bales in 1866 compared to 361,000 in 1858. Given the shortage of U.S. cotton, the increase in the relative quantity of Indian cotton was even greater. In the absence of directed technical change, it would be puzzling to observe similar relative prices in 1858, when there was a severe shortage of Indian cotton, and in 1866, when the relative availability of Indian cotton was at a historic high.

To analyze these patterns econometrically, I consider two separate questions. First, is there evidence that the relative price of Indian cotton behaved differently than that of the smaller alternative varieties that did not benefit from directed technical change? Second, is there evidence that the relative price of Indian/U.S. cotton rebounded to or above its pre-war level despite the increase in relative supply? Answering each of these questions requires a slightly different approach.

Answering the first question involves comparing price patterns across varieties, so it can be addressed using a panel data approach with data on the relative prices of Indian/U.S., Brazilian/U.S., and Egyptian/U.S. cotton.[46] The specification is,

$$\log(RP_{jt}) = \alpha + \left[\sum_{k=1859}^{1875} \gamma_k \times YR_k \times INDIA_j \right] + \Psi_j + \xi_t + Q_t + \epsilon_{jt} \tag{3}$$

where j designates a variety (Indian, Brazilian or Egyptian cotton), RP_{jt} is the price of the variety relative to the comparable U.S. variety, $INDIA_j$ is an indicator variable for Indian cotton, ϕ_j is a set of variety fixed effects, and ξ_t and Q_t are, respectively, sets of year and quarter effects.[47] Treatment coefficients are estimated for two pre-

[46]In this analysis, I compare Indian cotton to lower-quality U.S. cotton and Brazilian or Egyptian cotton to higher-quality U.S. cotton. One advantage of this is that these results are more robust to shifts in demand toward the lower or higher-quality market segments, an important concern since some such shifts may have occurred during the Civil War period. If I instead compare all of the alternative cotton varieties to the same type of U.S. cotton, the results are essentially unchanged.

[47]It is possible to include variety-specific time-trends in this specification. However, there is no

war years in order to look at pre-trends. In some specifications I also include an indicator variable for India in 1858-1859 in order to control for the impact of the Indian Rebellion on the relative price of Indian cotton. The data are quarterly and span 1852-1875. Estimation is done using Newey-West standard errors with a lag length of eight.[48]

The coefficient estimates and 95% confidence intervals are presented graphically in Figure 10, while full regression results are available in Appendix A.4.1. These results show no evidence of pre-trends. The relative price of Indian/U.S. cotton began diverging from the pattern shown by the comparison varieties in 1862. This difference widened in 1863 and persisted through the mid-1870s. These patterns are consistent with the impact we would expect from new technologies tailored to the use of Indian cotton.

The second question posed above involves comparing the response of the relative price of Indian/U.S. cotton during the Civil War to the pattern in the pre-war period. This naturally begs a time-series approach. The specification is:

$$\log(RP_t^{INDIA/US}) = \alpha + \left[\sum_{k=1859}^{1875} \gamma_k \times YR_k \right] + \epsilon_t \,. \tag{4}$$

There is no evidence of a time-trend in Figure 9, so a time-trend term is not included here. As before, I use quarterly data from 1852-1875 and calculate Newey-West standard errors with a lag length of eight (to cover two growing seasons). The results are presented in Figure 11. Compared to the pre-war period, we see a statistically significant drop in the relative price of Indian/U.S. cotton in 1862, followed by a rebound to the pre-war level in 1863. The relative price then remained at or above the pre-war level through the mid-1870's, with evidence of a statistically significant increase in several years in the late 1860s. This pattern is consistent with the strong induced-bias hypothesis.

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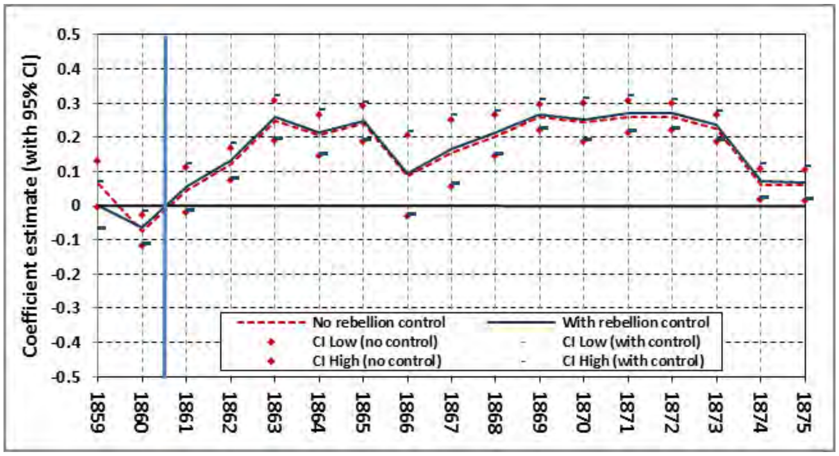
evidence of such trends in the pre-war period in Figure 9, suggesting that including these terms is not necessary. Moreover, with a somewhat short and volatile set of pre-war observations, including such time trends has the potential to substantially reduce the quality of the estimates.

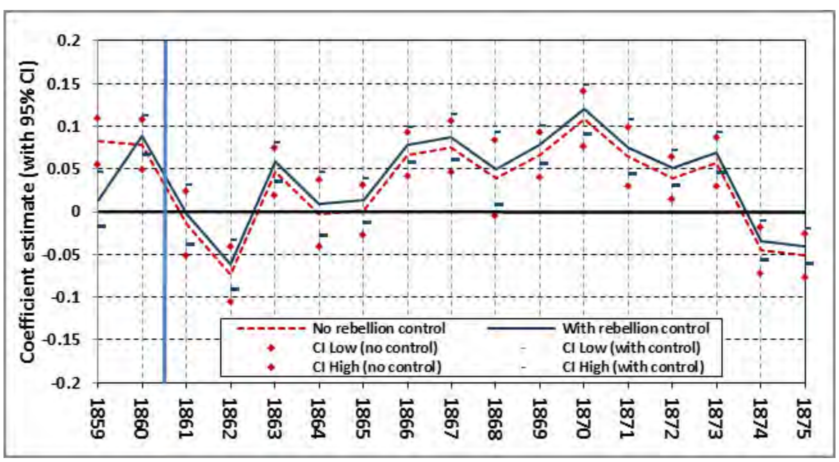
[48]The asymptotic properties of estimators of this type with fixed N and large T, or with both N and T growing, are studied by Hansen (2007). A lag length of 8 is used to allow correlation across two harvest seasons. This is larger than what Green's rule of thumb lag length $= T^{1/4}$ would suggest. I have experimented with using alternative lag lengths for these regressions and found that this does not substantially affect the statistical significance of the coefficients.

Figure 10: Pattern of India/U.S. cotton price relative to control varieties



Regressions compare the price response of Indian/U.S. cotton to two alternative varieties, Brazilian/U.S., and Egyptian/U.S. cotton. The data are quarterly and cover 1852-1875. The figure presents the estimated coefficient and 95% confidence intervals for variables interacting an indicator for each year starting in 1859 with an indicator variable for Indian cotton. Regressions use Newey-West standard errors with a lag length of eight. Regressions are done with and without controlling for the Indian Rebellion of 1858 using an indicator variable for Indian cotton in 1858-59.

Figure 11: Behavior of the Indian/U.S. cotton price relative to the pre-war period



Regression is run on a single time-series of the relative price of Indian/U.S. cotton using quarterly data from 1852-1875. The figure describes the coefficient and 95% confidence intervals for indicator variables for each year starting in 1859. Regressions use Newey-West standard errors with a lag length of eight. Regressions are done with and without controlling for the Indian Rebellion of 1858 using an indicator variable for 1858-59.

These results raise several potential issues that must be addressed. First, we may be concerned that the timing of the rebound in the relative price of Indian cotton occurs too rapidly, before the new innovations could have substantially affected the market. Yet, by the time the rebound began in October of 1862, many new technologies had already been patented, particularly in the carding and openers/scutchers categories, and gin patents had also reached a historic high. Market participants likely knew that further innovations were being developed. Given that information, and the fact that cotton was storable for up to a year, it is not surprising that market prices began reacting in 1862.

Another concern is that other time-varying shifts in the market, such as a shift in demand towards low-quality products, might have affected higher and lower-quality textile products differently. We may be worried that such a shift could cause the relative price of Indian cotton to behave differently than that of Brazilian or Egyptian cotton. However, recall that we are comparing the price of Indian cotton to the price of lower-quality U.S. cotton. A shift in demand toward lower-quality textile products would affect both of these varieties. The same argument applies to Brazilian and Egyptian cotton, higher-quality varieties that are compared to higher-quality U.S. cotton. Thus, it is unlikely that such a shift could be generating the patterns we observe, since it would be reflected in both the numerator and denominator of the relative price series.

Finally, we may be concerned that these results are generated by an upward shift in the quality of Indian cotton. However, recall that the prices of each cotton variety are reported *for a specific quality level.* Thus, shifts in cotton quality would be reflected in a reallocation of quantities across the fixed quality bins, but the quoted prices would continue to reflect the value of cotton at a fixed quality level. Moreover, rather than improving during the Civil War, the historical evidence suggests that the quality of Indian cotton actually declined during this period.[49] Thus, shifts in quality can be discarded as a likely explanation for the patterns we observe.

[49] For example, the *Bombay Saturday Review* (April 12, 1862, quoted from Logan (1965)), writes "the quality of Bombay cotton has notoriously become worse instead of better. The rise in prices has no other effect than of stimulating the practice of adulteration. Every trick... is used to swell the bulk and lower the intrinsic value of cotton. Sometimes the bales are wetted in the sea, sometimes their weight is increased by keeping seed in the cotton and loading it besides with stones and dirt, sometimes there is a systematic substitution of an inferior for a better kind of cotton, or a mixture of two kinds."

6 Conclusions

The study provides evidence that the temporary reduction in the supply of American cotton during the U.S. Civil War caused directed technical change focused on the main alternative input, Indian cotton. While similar, American and Indian cotton differed in important ways, and innovators focused their efforts on technology types that addressed these differences. Moreover, as these new technologies were introduced the relative price of Indian to U.S. cotton rebounded to (and perhaps above) the level observed during the pre-war period, despite a substantial increase in the relative supply of Indian to U.S. cotton.

Directed technical change theories, such as Acemoglu (2002), can potentially explain these patterns if the elasticity of substitution between U.S. and Indian cotton is sufficiently high (near 2), as suggested by Irwin (2003). Alternative theories may also have the potential to explain the patterns I identify. For example, perhaps innovators simply focused on reducing waste, and they focused on Indian cotton only because that was the main source of waste. However, we do not observe increased innovation in other major waste-producing technologies, such as combing machines, so this explanation seems unlikely. A more compelling alternative is that innovation may have been a result of learning-by-doing and the switch to production of machines more suited to Indian cotton. Differentiating between directed technical change and learning-by-doing is an interesting direction for future research.

My findings raise a historical question; what were the long-term impacts of this event? Total Indian cotton exports remained high from the Civil War to the drought and famine of the late 1870's. The high level of Indian exports was not reflected in British imports of Indian cotton due to the opening of the Suez Canal in 1869, which redirected Indian cotton toward spinning mills on the European continent. Given that textile spinning firms the world over were supplied by British machine makers, it may be that the primary beneficiaries of the new technologies developed during the U.S. Civil War were not British cotton spinners, but rather cotton textile producers in locations that were more dependent on Indian cotton, such as Japan, China, Continental Europe, and India itself. The long-term impact of the new technologies on these producers, and on Indian cotton farmers, is another avenue for future work.

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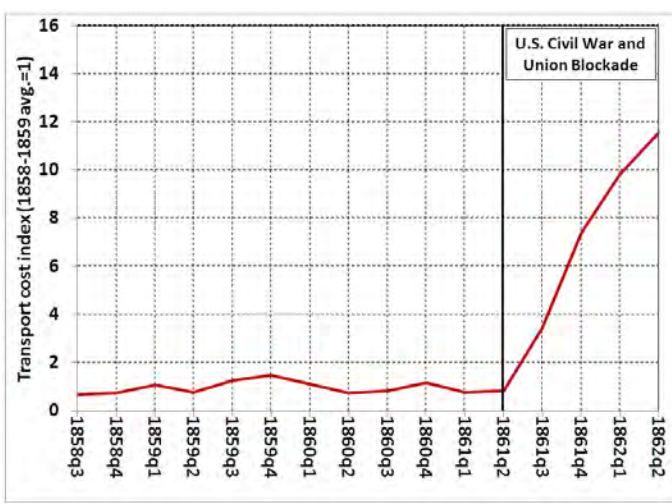
A Appendix (for online publication only)

A.1 Further details on the empirical setting

A.1.1 Increase in transport costs caused by the Civil War

The figure below shows an index of transport costs during the early part of the war constructed using the wedge between the cotton price in New Orleans, which was within the blockaded region until April of 1862, and the price in Liverpool.

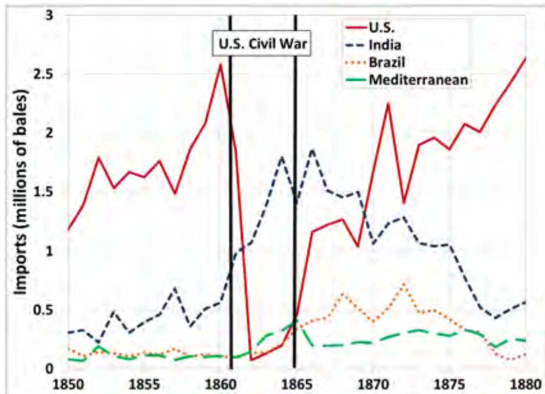
Figure 12: Effect of the Union blockade on the transport cost of cotton



Index constructed using price of Middling Orleans cotton from Liverpool and New Orleans. Liverpool prices collected from The Economist. New Orleans prices collected from the New Orleans Price Current and Commercial Intelligencer and converted to Sterling using the price of Sterling 60 day notes reported in the same. A similar pattern holds if New York prices are used in place of Liverpool prices.

A.1.2 Additional details on cotton supplies

Figure 13: Cotton imports by supplier 1850-1880



Data from Ellison (1886). Most of the imports from the Mediterranean would have come from Egypt.

A.1.3 Most innovative technology categories by patent count

Table 3: Top ten British Patent Office technology categories 1855-1883

Rank	Technology Category	Patents	Rank	Technology Category	Patents
1	Metals, Cutting, etc	7,017	6	Railway etc. vehicles	4,184
2	Furnaces	6,157	7	Steam generators	4,065
3	Preparatory & Spinning	6,009	8	Furniture	3,216
4	Steam engines	4,809	9	Mechanisms	3,120
5	Weaving & Finishing	4,807	10	Ships, Div. I	3,051

Top ten technology categories, by patent count, out of the 146 total British Patent Office technology categories. “Preparatory & Spinning” includes machinery used in the preparatory and spinning stages of production. “Weaving & Finishing” includes machinery used in the weaving and finishing stages.

A.1.4 Definitions of important textile terms

The following definitions were constructed with the aid of *The "Mercury" Dictionary of Textile Terms*. 1950. Textile Mercury Limited: Manchester, England.

Carding- A very thorough opening-out and separating of the fibers of cotton, together with an effective cleaning. This machine is the last where cleaning the cotton takes place (unless the cotton has to be combed).

Combing- This term is used literally and denotes the combing of fibrous materials in sliver form by mechanically actuated combs or by hand-operated combs. In general, the objectives in combing are two, namely (1) to obtain the maximum parallelization of the fibers and (2) to remove impurities and undesired short fibers.

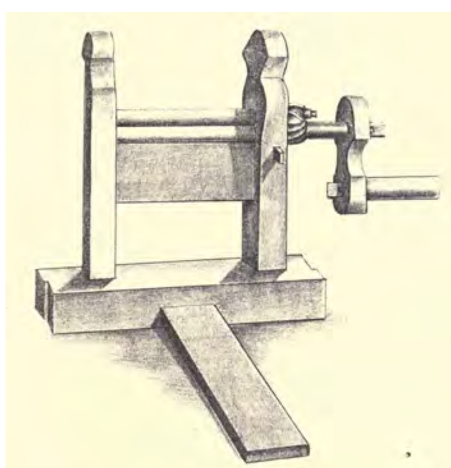
Gin- A cotton cleaning machine with the primary purpose of separating the cotton seeds from the cotton fibers.

Opening cotton- This is done on machines (openers) which beat the cotton into a more fleecy condition and also remove a good proportion of the dirt and heavier impurities.

Scutching- An operation in preparing cotton for spinning that has three objects, to reduce the cotton to a loose open condition by beating it, removal of impurities remaining in the cotton after opening, and the formation of a continuous lap or web of cotton wound on to a rod–which laps go forward to the carding engine.

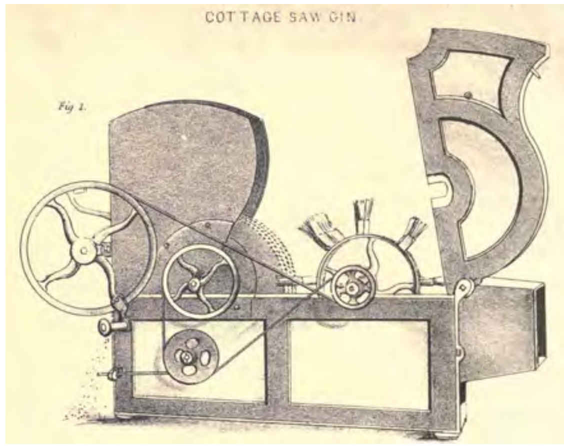
A.1.5 Cotton textile machinery

Figure 14: Indian Churka for removing cotton seeds



Reproduced from Wheeler (1862).

Figure 15: Cottage Saw Gin



Reproduced from Wheeler (1862).

Figure 16: Dobson & Barlow Opener circa 1920

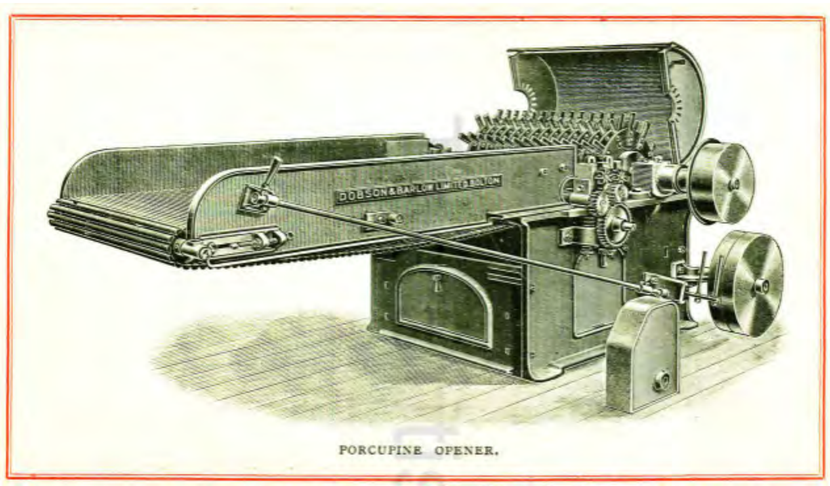


Figure 17: Dobson & Barlow Scutcher circa 1920

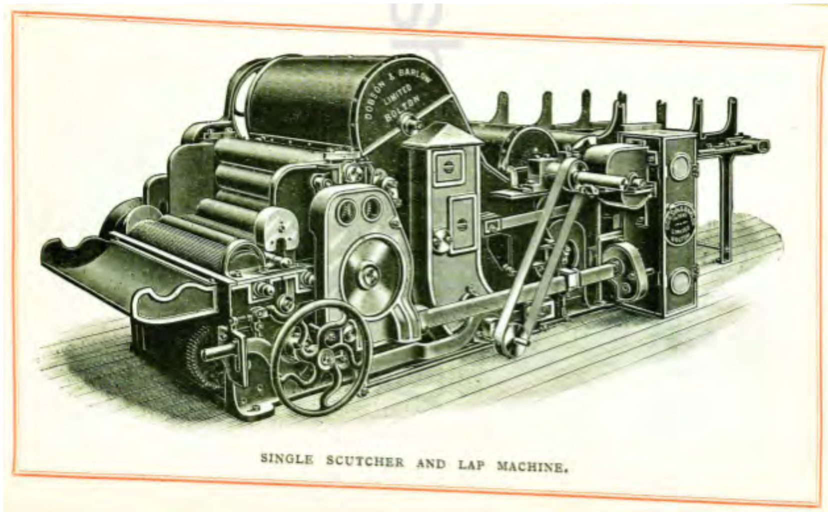
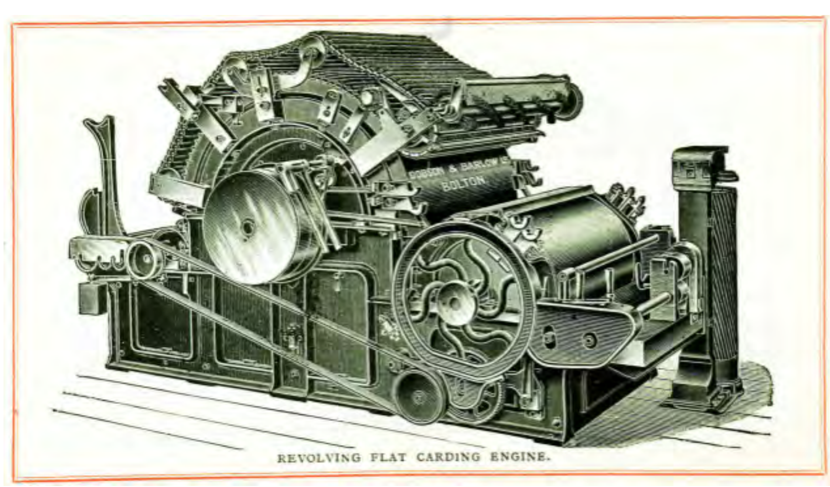
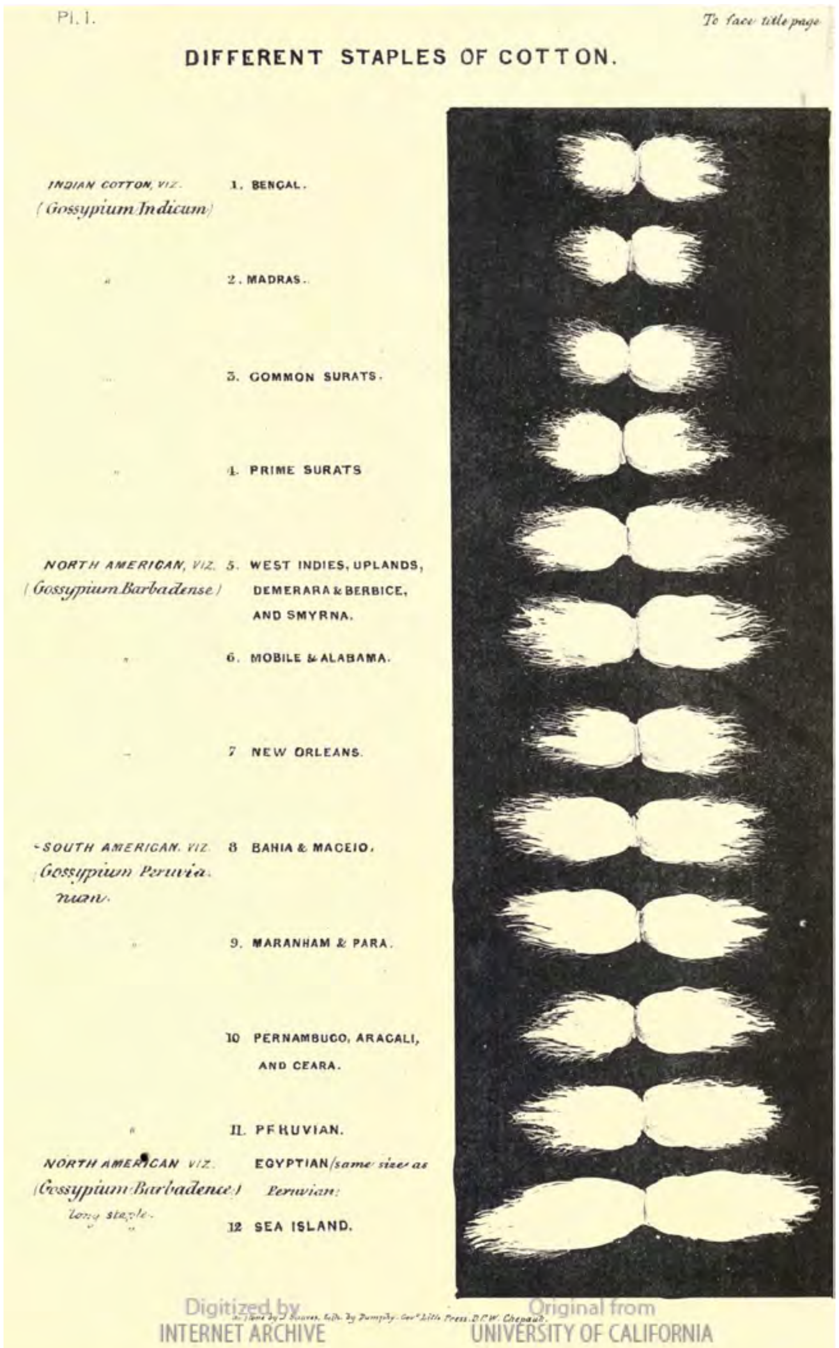


Figure 18: Dobson & Barlow Carding Machine circa 1920



A.1.6 Details on the differences between cotton types

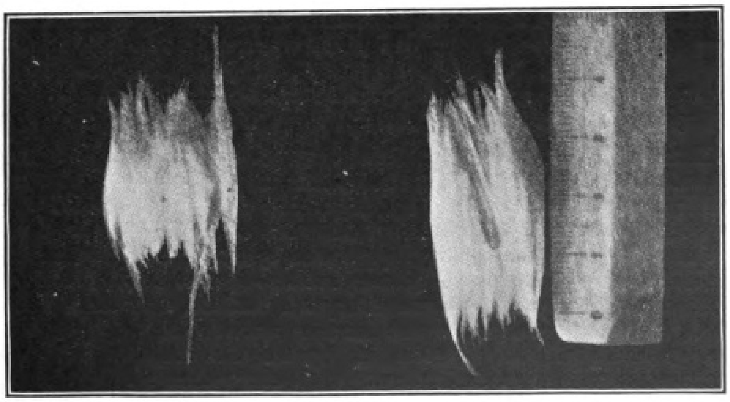
Figure 19: Length of cotton staples for various cotton types



Reproduced from Wheeler (1862).

A.1.7 Impact of ginning on cotton fiber length

Figure 20: A comparison of ginned (left) and hand-cleaned cotton (right) fiber length



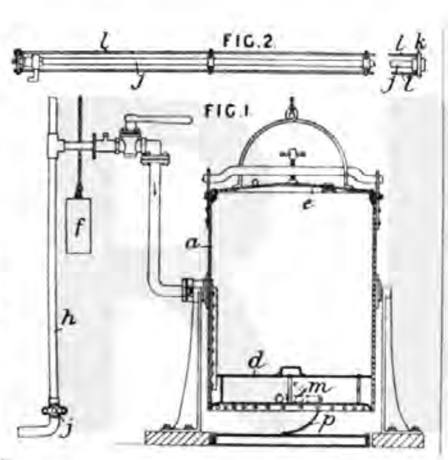
Reproduced from Pearse (1921).

A.1.8 Example patent specifically mentioning Indian cotton

Figure 21: An Example: Patent No. 2162 from 1862

2162. Wanklyn, W. July 30.

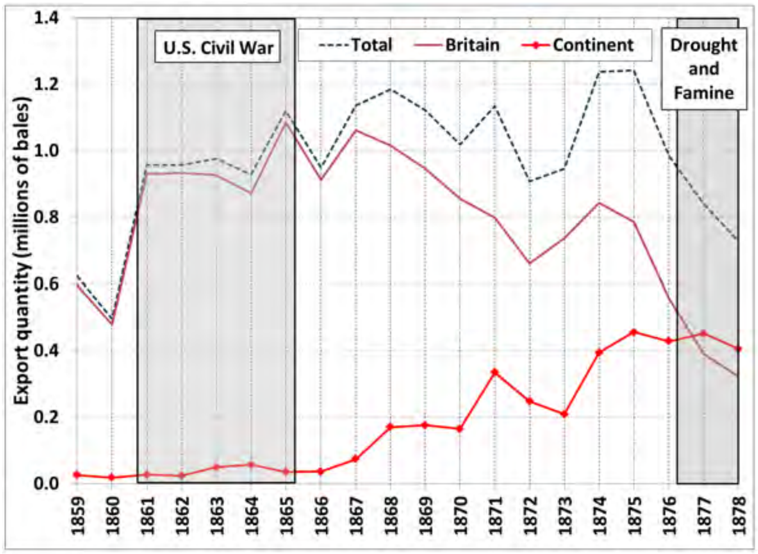
Steaming fibres ; openers, cleaners, &c.—Relates to apparatus for opening and conditioning East Indian and other tightly-compressed cotton, sheep's wool, &c. by steaming. The cotton is transferred from the bale to a vessel *a*, which is mounted on trunnions, and is provided with a perforated false bottom *d* and a tightly-fitting lid *e* balanced by the counterweight *f*. Steam under pressure is admitted to the space below the perforated false bottom, and after the material has been submitted to the action of the steam for about a minute, the steam is shut off, the lid *e* removed and the vessel *a* tilted so that the cotton may be raked into a truck &c. and taken to the opening-machine. A suitable prop is provided for holding the vessel *a* in the tilted position, and the act of tilting the vessel opens by means of a chain *p* an escape valve *m* for condensed water. In order that condensed water may be excluded as much as possible from the vessel *a*, the steam pipe *h* is connected with a horizontal pipe *j* in which is a valve connected by rods *l* with a crosshead *k* on the end of the pipe. So long as the pipe *j* is sufficiently heated by the steam, the valve is closed, but when the pipe is cooled by the accumulated condensed water, the valve is opened and the water escapes.



From *British Patent Abstracts, Class 120, 1855-1866.* Available from the British Library.

A.1.9 Indian cotton exports

Figure 22: Indian cotton exports, showing Britain and the Continent



Data collected from from Statistical Abstracts of British India.

A.2 Data appendix

A.2.1 Overview of the patent data

Modern patent data has been widely used in recent studies of innovation, building on seminal work by Schmookler (1966), Scherer (1982), Griliches (1984), and Jaffe *et al.* (1993). Hall *et al.* (2001) provide a helpful review of the advantages of using patent data, including that (1) patents contain highly detailed information, (2) there are a large number of patents available to study, and (3) patents are provided on a voluntary basis under a clearly defined set of incentives. This study is able to take advantage of thousands of patents and draws heavily on the detailed information available in the patent descriptions.

One disadvantage of using patent data is that it does not capture all types of innovation. Evidence from Moser (2012) shows that a significant fraction of new inventions went unpatented during the period I study. However, her results also suggest that, among all categories, inventions of manufacturing machinery – the primary focus of this study – were the most likely to be patented. Moser (2012) finds that of those innovations exhibited in the Crystal Palace exhibition in 1851, 29.8% of manufacturing machinery exhibits were patented compared to an average of 11.1% over all exhibit types. Of the exhibits receiving prizes, 47.1% of manufacturing machinery exhibits were patented compared to an average of 15.6% across all exhibit types. Note that a significant patent reform was undertaken in 1852 which simplified the process for obtaining patent protection while greatly reducing cost of patenting. The result was a sharp increase in patents from hundreds to thousands. Thus, these percentages are likely to have been significantly higher during the period I study. The incentive to patent appears to have been particularly strong for textile machinery, which was relatively easy to reverse-engineer. Thus, this concern appears to be less important in the context studied here. A second concern is that patent counts may not reflect the underlying quality of the new inventions, which can vary widely. This concern is addressed using several measures of patent quality.

Much of the data used in this study was collected for the purpose of this project from around 1,500 pages of printed British patent records. To begin, I constructed a database covering all of the patents granted in Britain between 1855 and 1883, 118,863 in all. Each patent is classified into one or more of 146 technology categories by the British Patent Office (BPO). These classifications allow me to identify the type of technology underlying each patent. The purpose of this categorization was to aid inventors in identifying previously patented technologies. My focus is on the two BPO categories related to textile production, "Preparation & Spinning" and "Weaving & Finishing". The British Patent Office calls these categories Spinning and Weaving, but I use these names to make it clear that the preparatory machines are included in the spinning technology category.

These data include both granted patents and those which received provisional protection but where a patent was not ultimately granted. However, because the British patent system did not include a patent examination at this time, substantially all of the patents applied for appear to have been granted. The validity of the patent could then be challenged *ex post* in the courts.

These data are supplemented with information from the *A Cradle of Invention* database, which has been used in previous research (e.g., Brunt *et al.* (2012)).[50] This database provides the titles of the patents, which are not available in the patent data I collected.

A.2.2 Data on spinning technology subcategories

To track innovation patterns in specific textile spinning technologies, I use BPO subcategories within the BPO Spinning technology category. Within this category, the BPO classifies patents into one or more technology subcategories and often into sub-subcategories. I have collected data on all substantial technology subcategories within the Spinning technology category.

[50] I thank Tom Nicholas for suggesting this data source. These data are available through MFIS LTD (finpubs.demon.co.uk). These data match the primary database well, with over 98% of patents in the two databases matching.

An important concern in these data is that some of these subcategories (and sub-subcategories) are so detailed that they contain few patents. This requires a decision about how small a control technology subcategory can be and still be useful. For the data used in the main analysis, I include only control technology types that were important enough to receive at least one patent in each year. This bar is low enough to obtain a reasonable number of control technology groups. At the same time, not having zero patent in any year in the control technology groups allows me to use the same set of groups for the analysis of the time-path of patents in Figure 5 as were used in the main results in Table 1 without having to worry about losing observations when taking logs. Patents fitting into the smaller technology categories are included in the main analysis in a residual technology category, "Uncategorized spinning patents". In the robustness exercises I explore how the results change when I break out these smaller technology categories. I find that breaking out these smaller technology subcategories does not substantially affecting the results.

A second issue with the data is that some of the technology subcategories are explicitly for textiles other than cotton. The most common example are technologies related to the preparation of flax for use in producing linen. Since my primary focus is on shifts occurring within the cotton textile industry, I omit these technologies from the main analysis, though I also assess the impact of including these in the robustness exercises.

Table 4: Preparatory & Spinning technology subcategories

Major Preparatory & Spinning technologies (used in main analysis)

Preparatory machines	**Patents**	**Spinning machines**	**Patents**
Gins*	122	Mules and twiners	446
Openers/scutchers	331	Spinning/twisting machines	1013
– *Applicable to cotton**	195	Winding machines	341
– *Others*	135	Drawing frames	153
Carding	696	Lap forming machines	73
– *Dirt/debris removal**	53	**General spinning technologies**	**Patents**
– *Others*	643	Bobbins	265
Combing machines	354	Spindles (includes bearings)	720
Gill boxes	187	Processes	536
Motions	**Patents**	Rollers for spinning	462
Building motions	257	**Yarn and finishing**	**Patents**
Stop motions	267	Yarns	218
Winding-on motions	190	Finishing of yarn	332
Uncategorized	**Patents**		
Uncategorized spinning patents	770		

Smaller categories (used only in robustness analysis)

Carbonizing fibers	72	Cards (wire)	89
Lubricating fibers	86	Reeling machines	90
Feeding carding machines	73	Fiber treatments	72
Twist tubes	97		

Categories for non-cotton textiles (used only in robustness analysis)

Retting machines	128	Heckling machines	157
Flax breaking machines	223	Flax feeding machines	86
Obtaining fibers (special materials)	168	Fibers for special articles	62

Categories marked with a * were the most important for using Indian cotton. Patent counts for BPO Preparatory & Spinning technology subcategories, 1855-1876.

A.2.3 Identifying patents related to Indian cotton

Historical accounts of the use of Indian cotton during the study period indicate that the major challenges faced by users was removing the seeds from the Indian cotton, opening the fibers which had been tightly compressed for their journey, and removing sand, dirt, leaves, and other debris from the cotton. These processes were done using gins, openers, scutchers, and carding machines. Gins focused on removing the seeds, openers opened the compressed fibers so that they could be handled by later machines, and scutchers and carding machines helped clean the fibers.

While openers and scutchers were important for the use of cotton, variations of these machines also had applications to other textile inputs. In particular, different versions of these machines were used to prepare flax and to tear up waste rags for re-spinning. Some patents were for even more exotic inputs, such as oakum, silk rags, reed grass, and piassave (also known as monkey grass). Some patented technologies within this category were specialized for cotton or were applicable to all types of machines, while others were specialized for other uses. It is important to separate these out, since only patents related to cotton or generally applicable should be included in the treated technology category. To do this, I reviewed the abstract of all 331 patents of openers/scutchers. These abstracts, similar to an abstract for an academic paper, contain a brief overview of the patent, usually in 1-3 paragraphs. Patents that mentioned another input and did not mention cotton were classified as "Openers/scutchers – non-cotton". Patents which specifically mentioned cotton, and patents which did not mention any specific type of input, were treated as being applicable to cotton and classified into the "Openers/scutchers – cotton" category.

Carding machines formed an important part of spinning mill machinery during the study period. While carding machines could be improved in many ways, the most relevant improvement for the use of Indian cotton would have been technologies related to removing dirt and other debris from the raw fibers. These were large and complex machines and as a result patents in the carding machine subcategory were divided by the British Patent Office into a number of technology sub-subcategories. Among these subcategories, the BPO identifies two that are specifically related to dirt removal. Their titles are "dirt, waste and the like, collecting and removing" and "dirt-knife arrangements". The classification of patents into "Carding – dirt removal" is based on these two sub-subcategories, while all other carding patents are included in the "Carding – other" category.

A.2.4 Details of the British patent system between 1852 and 1883

There were no major changes in the British patent system between 1852 and 1883. During this period, patent applications cost £25, which was considered a substantial sum at the time. This amount was roughly equal to £1,840 2009 pounds, when deflating by the retail price index, or £16,300, when deflating by average earnings (calculator available at from the Measuring Worth project at www.measuringworth.com). For comparison, the fee was reduced to only £4 as a result of the 1883 patent law. Applications were also a lengthy and complicated process.

This study focuses on the filing of preliminary patent applications. These preliminary applications were easier to submit; they could be made using only basic information on the invention. The application provided the applicant with provisional protection and could aid them in establishing the seniority of their invention. The applicant was then responsible for supplying full patent specifications within six months or the patent became void. Patents lasted for 14 years but renewal fees had to be paid at years three and seven in order to keep the patent in force. These fees were even more onerous than the initial application fee; applicants had to pay £50 after three years and another £100 after seven years to keep their patents in force.

At this time, the British patent system did not include an official examination, such as the one we are familiar with today. Instead, the validity of patents was mainly established through *ex post* litigation. As a result, substantially all of the patents applications in the data would have been sealed (i.e., granted) unless the applicant failed for provide a final specification or to undertake the necessary bureaucratic steps. For more information on the British patenting system during this period see Van Dulken (1999) and Khan (2005).

A.2.5 Details on inventors in the patent database

Table 5: Details of individual spinning and cotton technology inventors

Spinning technology inventors, 1855-1883			
Number of inventors	Number of inventor x patent obs.	Median patents/inventor	Mean patents/inventor
5038	9744	1	1.934101

Cotton technology inventors, 1855-1870			
Number of inventors	Number of inventor x patent obs.	Median patents/inventor	Mean patents/inventor
1384	2144	1	1.549133

A.2.6 Further details on the patent quality measure data

This section describes the three measures of patent quality used to evaluate whether the 1861-1865 period was also characterized by an increase in the number of high-quality cotton-textile-related patents.

Valuing patents using renewal data

During the period covered by this study, British patents lasted for 14 years, but in order to keep them in force patent holders were required to pay renewal fees of £50 before the end of three years and an additional £100 before the end of seven years.[51] These were substantial sums at the time and the result was that the vast majority of patents were allowed to expire before their full term. My data show that just under 18% of patents were renewed at three years, while just over 6% were renewed at seven years. Thus, paying a renewal fee represents a substantial investment which would only have been worth it for a small set of the most successful technologies.

[51]For comparison, £100 in 1860 is equivalent to £7,020 2010 pounds using a retail price index deflator, or £65,2000 when deflating by average earnings (calculator available through the Measuring Worth project at www.measureingworth.com).

Renewal fee data were gathered from listings in *Mechanics' Magazine*, a weekly periodical focusing on patents and related topics. The magazine is available from the end of 1858 to the end of 1872, so that data on renewals at year three are available for patents filed from 1856-1869 and data on renewals at year seven are available from 1853-1865. By merging the renewal data with the primary patent data set, it is possible to track renewal patterns for textile-related patents.

Valuing patents using contemporary publications

A contemporary periodical can be used to highlight the interest or excitement generated by a new patent upon its publication. The data I use were collected from *Newton's London Journal*, a monthly publication devoted to covering new patents and other technology-related topics. This journal was published by William Newton & Sons, one of the preeminent patent agents in London. Among the *Journal's* stated goals was making more easily available the information contained in patent filings, and to this end, each issue included abstracts from a selection of recently sealed (i.e., granted) patents, some of which were accompanied by detailed drawings. It is worth noting that patent abstracts were only included after the patent had been sealed, so publication was often as long as a year after the initial patent application was filed. This means that the editor would have had some perspective from which to judge the influence of a patent before including it in the journal. Though the publishers provide little information about the criteria used to select these patents, presumably they included those patents which were deemed by the editors to be the most important inventions, or those which would be of greatest interest to the readers. Thus, inclusion of a patent abstract in the journal is treated as an indication of the initial novelty of each patent, based on the judgment of a knowledgeable contemporary opinion.

The *Journal* is available from January 1855 - February 1866, meaning that any patent applied for from 1854-1864 should have been a candidate for inclusion. Matching these patents to the primary patent database allows me to identify patents of textile and cotton related technologies. The analysis is based on the date the patent was filed, rather than the publication date, so for example, I look at all patents which were filed in 1861 and then subsequently published, and analyze the share composed of textile-related patents.

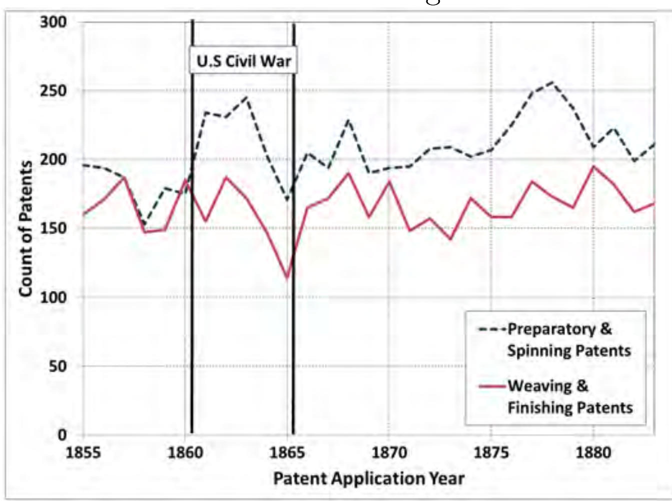
A.3 Appendix to the Empirical Analysis Section

A.3.1 Analysis of patent data

To begin, I motivate the focus on innovations occurring in the Preparation & Spinning technology category by showing that it was these early-stage production technologies that responded strongly during the Civil War period. The figure below illustrates that impact of the Civil War on the two key textile technology categories, Preparatory & Spinning and Weaving & Finishing in the top panel, and on all of the other 144 BPO technology categories, in the bottom panel, using annual data from 1855-1883.

Figure 23: Patenting behavior over the study period

Textile technologies

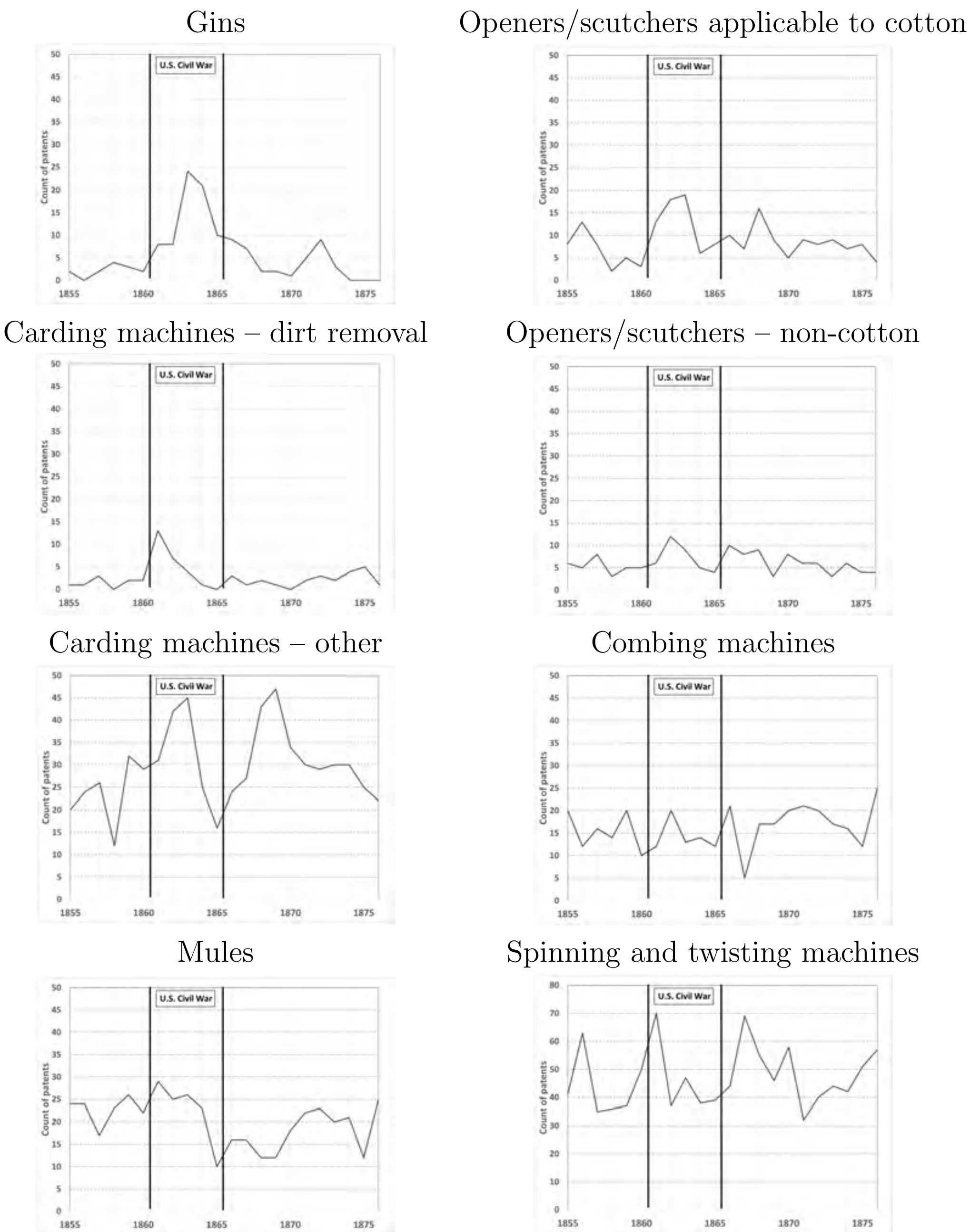


All other technology categories

Annual data for 1855-1883 collected from British patent subject abstracts.

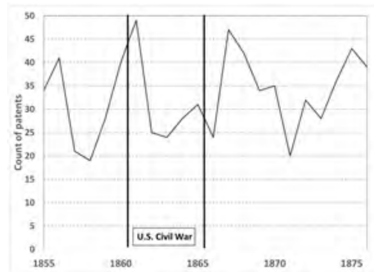
Next, I provide individual graphs for each of the technologies subcategories in the Preparatory & Spinning technology category that are used in the main analysis.

Figure 24: Patents in Preparatory & Spinning technology subcategories



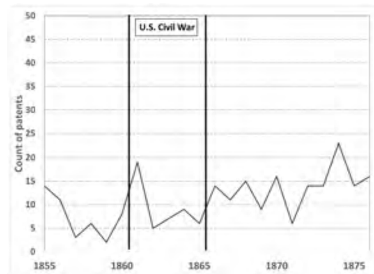
Stop-motion mechanisms

Spindles



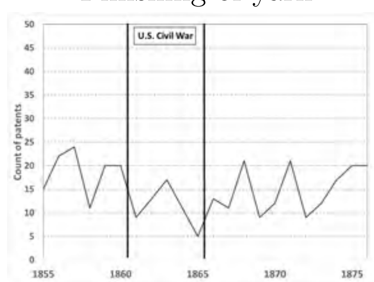
Rollers

Bearings

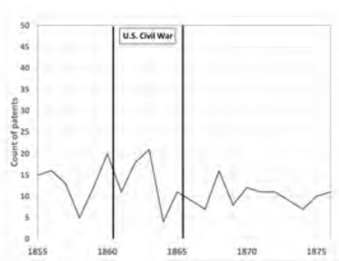


Winding machines

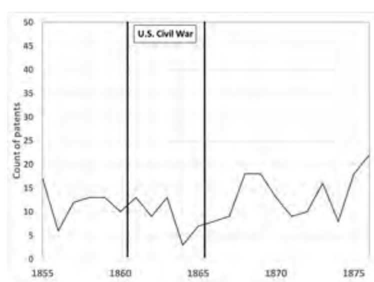
Finishing of yarn



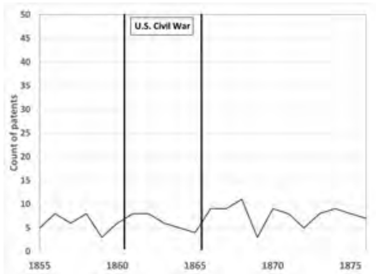
Building motions



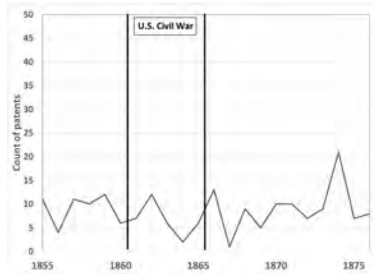
Bobbins, etc.



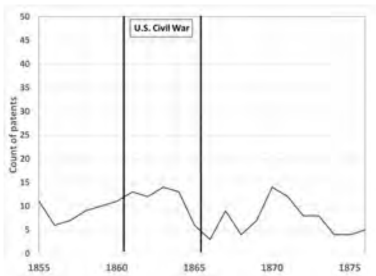
Drawing frames



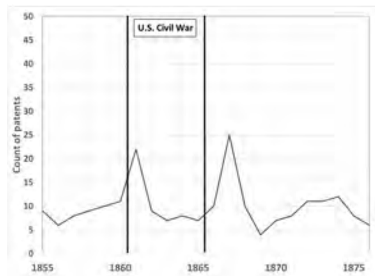
Gill boxes



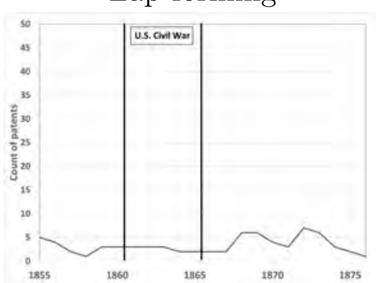
Winding-on motions



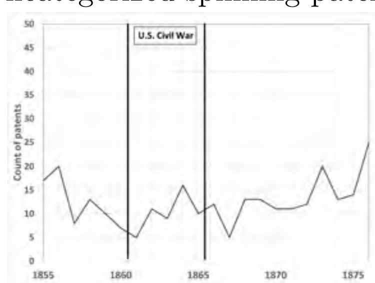
Yarns



Lap forming



Uncategorized spinning patents

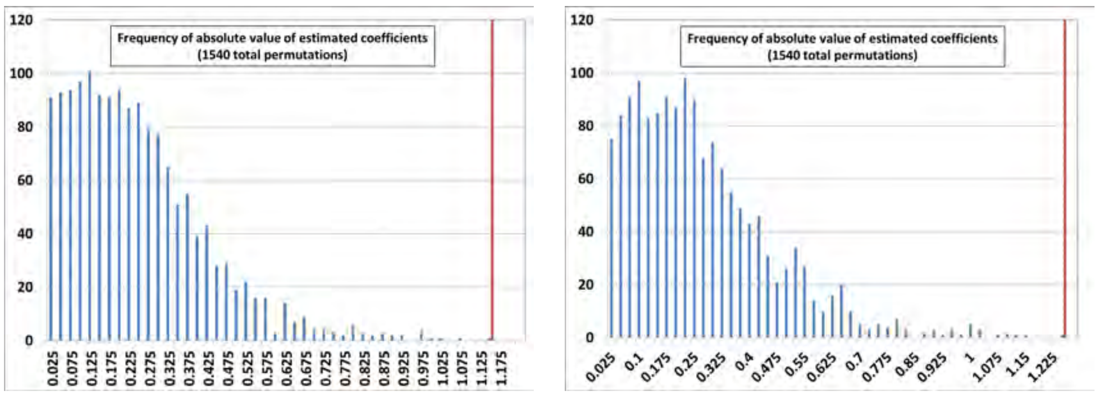


*The uncategorized spinning patents technology category excludes technologies explicitly for textiles other than cotton.

The results in the main text based on the permutation approach are strong. To help us understand these results, the next graph provides a histogram of the distribution of the estimated placebo coefficients based on the control technology groups compared to the estimated coefficient from the India-related technologies.

Figure 23: Histogram of permutation-based coefficient estimates for main results (Table 1)

Column 1 of Table 1 Column 2 of Table 1



This figure compares the distribution of the absolute value of the coefficient estimates from regressions run with every permutation of 3 out of the 22 technology categories are treated as the three treatment categories. There are 22 technologies so there are 22 choose 3 = 1540 placebo coefficients. The line on the right indicates the coefficient estimate from the actual India-related technology groups.

Next I conduct some exercises exploring the robustness of the results to the inclusion of different control technologies. In the data set used in the main analysis, a number of small technology subcategories are aggregated into a single residual category. Also, four larger technology subcategories were excluded because those technologies were not applicable to cotton. In columns 1-3 of the table below I add back in just the small technology subcategories (Column 1), just the larger non-cotton technology subcategories (Column 2), and both (Column 3) and show that the results are essentially unchanged. Another potential issue with the data is that some patents are listed in more than one technology subcategory. Of the 4,174 patents included in the main analysis, 1,832 of them are cross-listed into multiple technology subcategories. Dropping these leaves us with a database of 2,342 remaining patents. The results in Column 4 show that excluding these cross-listed patents weakens the results, but that in general they continue to be statistically significant. Note that one technology, “Winding-on Motions” does not have any patents that were not cross listed and therefore has been dropped from the analysis. The last column presents results obtained when I include only patents with “cotton” in the title in the estimation data.

Table 6: Robustness to variation in underlying data

	Dependent variable: Log Patents				
	With 8 smaller subcategories	**With 4 non-cotton subcategories**	**With smaller and non-cotton subcategories**	**Dropping cross-listed patents**	**Patents with cotton in the title**
	(1)	(2)	(3)	(4)	(5)
India-related	1.204	1.080	1.143	1.098	1.139
x Shock period	(0.275)	(0.275)	(0.273)	(0.313)	(0.344)
	[0.000]	[0.000]	[0.000]	[0.002]	[0.003]
	[[0.038]]	[[0.051]]	[[0.044]]	[[0.048]]	[[0.089]]
Subcategory effects	Yes	Yes	Yes	Yes	Yes
Time period effects	Yes	Yes	Yes	Yes	Yes
Observations	90	78	105	63	66
Number of panels	30	26	35	21	22

All regressions include the pre-shock, shock, and post-shock periods. Column 1 includes data from 8 smaller technology subcategories. Column 2 includes data from 4 non-cotton technology subcategories. Column 3 contains both smaller subcategories and non-cotton subcategories (including smaller non-cotton subcategories not included in columns 1 and 2). **Parentheses** contain robust standard errors. **Single brackets** contain p-values from a permutation-based approach in which I select every permutation of three technologies out of the available technology categories and estimate the impact on these three during the shock period. The distribution of these "placebo" coefficients is then used to construct the p-value of the treatment coefficient. **Double brackets** contain p-values from a test based on HC2 standard errors tested against a t-distribution with a degrees of freedom determined using Welch's (1947) formula.

We may be interested in separating out the effects on the different technologies related to Indian cotton. The regressions presented below do this by estimating a separate coefficient for each of these technology subcategories. The regression specification is,

$$\begin{aligned}\log(PAT_{jt}) = \alpha \quad &+ \quad \beta^{Gins}(S_t \times GINS_j) + \beta^{Open}(S_t \times OPENERS_j) \\ &+ \quad \beta^{Card}(S_t \times CARDING_j) + \Psi_j + \xi_t + e_{jt},\end{aligned}$$

where $GINS_j$ in an indicator variable for gin technologies, $OPENERS_j$ is an indicator variable for openers/scutchers related to cotton, and $CARDING_j$ is an indicator variable for carding innovations for dirt removal. An important constraint in conducting this exercise after aggregating to pre-shock, shock, and post-shock periods is that we have three explanatory indicator variables that take a value of 1 only once, and are zero otherwise. This raises an issue with the small-sample adjustments that I have used. In this context, the permutation-based approach has only 19 estimated coefficients, one for each control group, to work with. With such a small number it is not clear we can get a reasonable estimate of the distribution of the coefficient estimates. The alternative approach, based on Imbens & Kolesar (2012), is also inapplicable in this setting because it cannot accommodate these indicator variables. See Angrist & Pischke (2009) (p. 320, footnote 17) for a discussion of this point. Thus, I present these results without accompanying small-sample adjustments. They should be taken as merely suggestive since we cannot be sure how precise these estimates are.

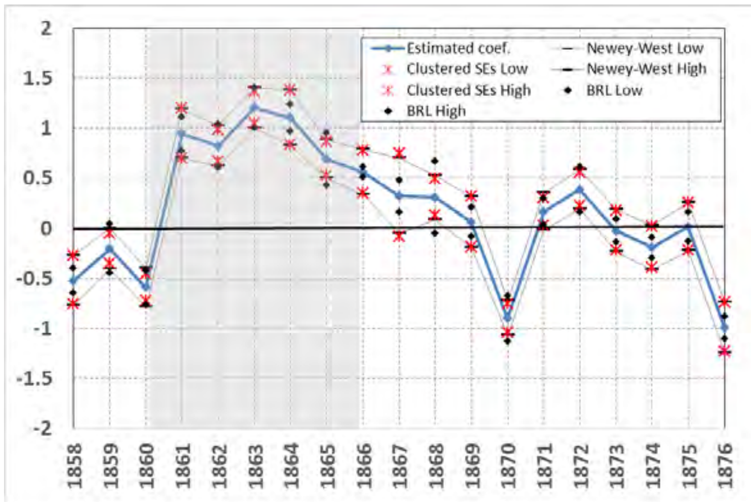
Table 7: Regressions with separate coefficients for each Indian-related technology

	Dependent variable: Log Patents	
	Comparing shock period to pre and post-periods	Comparing shock to pre-period only
	(1)	(2)
Gins	1.703	1.880
x Shock period	(0.052)	(0.054)
Openers for cotton	0.607	0.678
x Shock period	(0.052)	(0.054)
Carding dirt removal	1.072	1.204
x Shock period	(0.052)	(0.054)
Subcategory effects	Yes	Yes
Time period effects	Yes	Yes
Observations	66	44
Number of panels	22	22

Column 1 uses data from the pre-shock, shock, and post-shock periods which are, respectively, 1855-1860, 1861-1865, and 1866-1876. Column 2 uses only data from the pre-shock and shock period. **Parentheses** contain robust standard errors.

Next, I turn to some robustness checks on the timing regressions presented in Figure 5. Here serial correlation is potentially a substantial concern. In addition to the Newey-West approach used in the main text, there are several other candidate approaches for dealing with serial correlation. One potential approach in the literature is to cluster standard errors by technology category. A concern with that approach is that there are only 20 clusters, so the standard errors may be understated. Another approach that aims to deal with the small number of groups is the Bias Reduced Linearization from Bell & McCaffrey (2002), which has previously been implemented by Angrist & Lavy (2009). Figure 24 presents the resulting coefficients and confidence intervals. It is clear that these alternative methods all deliver nearly identical results.

Figure 24: Comparing various methods for annual regressions



This figure presents coefficient estimates and standard errors based on the specification in Equation 2, where patents from the three India-related technologies have been aggregated within each year. Standard errors are based on (1) Newey-West with a lag length of 3, (2) clustering by technology category, and (3) the Bias Reduced Linearization approach as in Angrist & Lavy (2009).

A.3.2 Analysis of high-quality patents

This section presents some additional information related to the analysis of high-quality patents. The first two graphs describe the patenting patterns for high-quality patents.

Figure 25: Patents renewed after three years

Indian-related technology patents | Ratio of Indian-related / all others

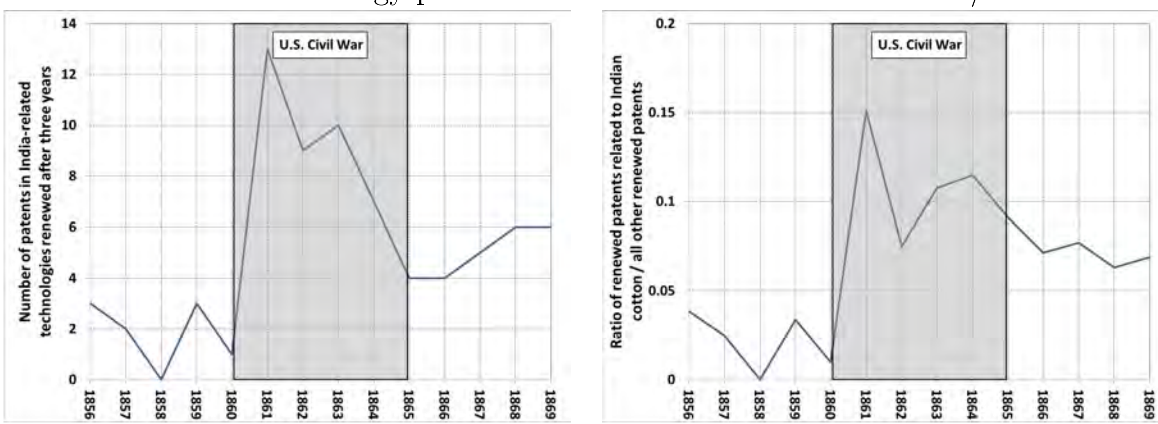
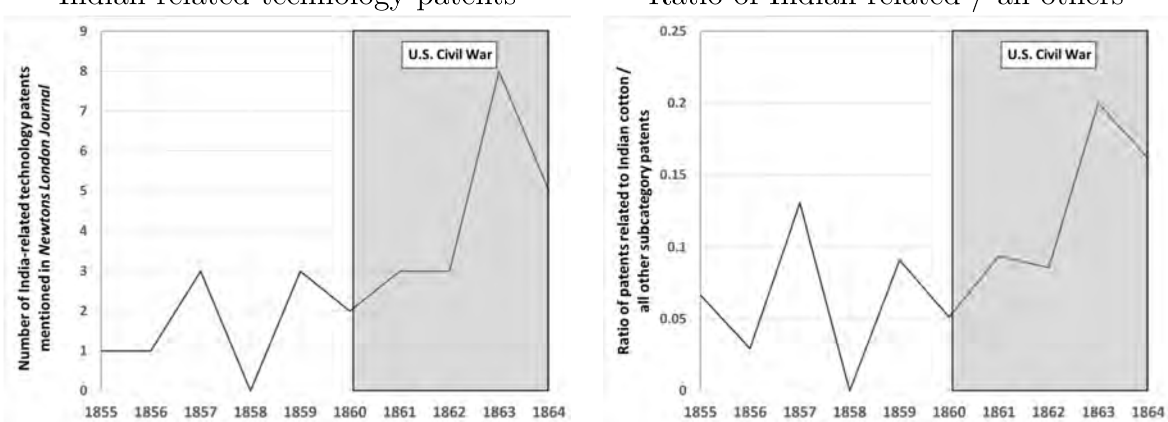


Figure 26: Patents mentioned in *Newton's London Journal*

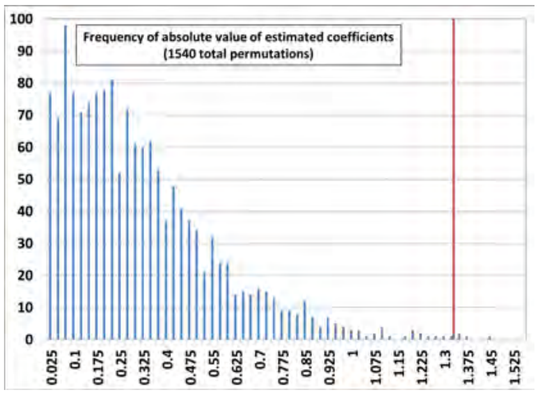
Indian-related technology patents | Ratio of Indian-related / all others



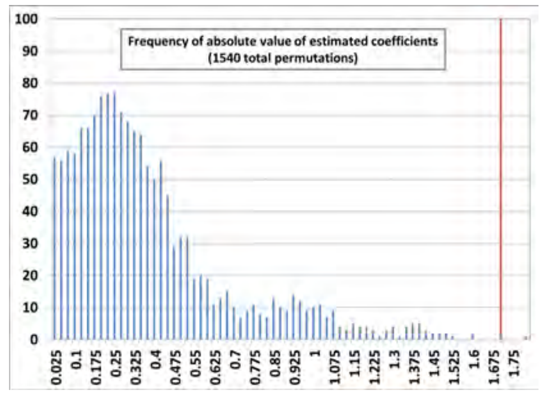
The next set of graphs present the distribution of coefficients used in the permutation-based inference exercises with high-quality patents.

Figure 27: Histogram of placebo coefficients for high-quality patent results (Table 2)

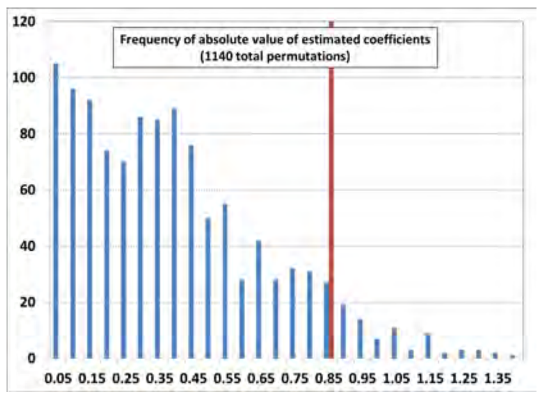
Column 1 of Table 2



Column 2 of Table 2



Column 3 of Table 2



These figures compare the distribution of the absolute value of the coefficient estimates from regressions in which every permutation of 3 out of the available technology categories are treated as the three treatment categories. For columns 1 and 2 there are 22 technologies so there are 22 choose 3 = 1540 placebo coefficients. For column 3 there are 20 technology categories and therefore 1140 coefficients. The lines on the right indicate the coefficient estimate from the actual India-related technology groups.

A.3.3 Dobson & Barlow graphs

The graphs below show the level of orders for gins, openers/scutchers, and carding machines from the Dobson & Barlow order books. As Dobson & Barlow's experience with each machine type is slightly different I discuss each in turn.

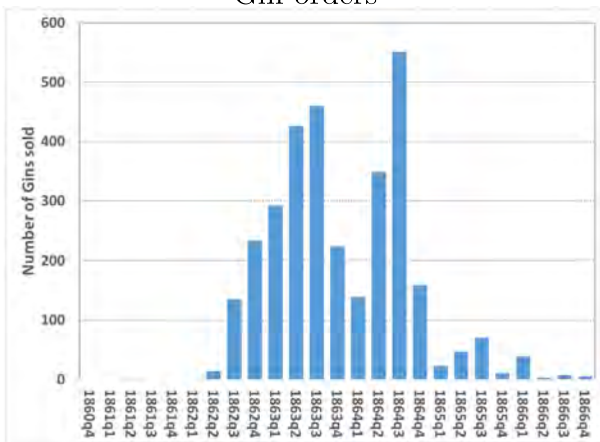
For gins, Dobson & Barlow was not active in the market prior to the Civil War (at least in the available data). The shift to alternative suppliers during the Civil War period generated enormous demand for gins, since the available gins in all locations were too few to gin the rapidly expanding crops, while existing gins were stuck in the American South. Thus, gins became an important product for Dobson & Barlow during the Civil War period. At first this appears to have been done using publicly available designs, though by 1863 Dobson & Barlow began patenting their own designs. These gins were shipped to a variety of buyers. Many were British firms, which presumably acted as traders, shipping the gins to third markets such as India. Dobson & Barlow also sold to the Cotton Supply Association, which shipped gins to a variety of locations for experimentation. Other orders went directly to places including Egypt, Turkey, Syria, and Brazil.

For openers/scutchers (which also includes related lap machines), the number of orders is presented relative to the number of mule orders. This is done to control for the general fall in sales of most spinning machines during the Civil War period. In normal times, openers/scutchers would be installed in mills alongside other spinning machinery in roughly similar proportions. Thus, the high relative level of openers/scutcher sales we observe is consistent with additional investment in these machines during the Civil War period.

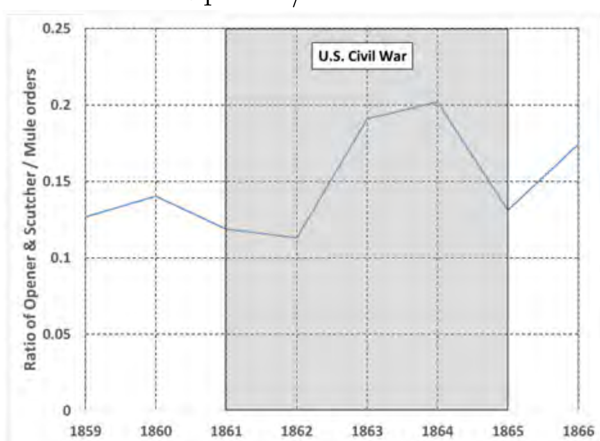
The pattern for carding machine sales is particularly interesting. As with openers/scutchers, I divide carding machine sales by the number of mules sold to account for the overall drop in investment during the Civil War. The interesting feature for carding machines is that we observe a large number of orders for alterations of existing machines to incorporate cutting edge carding technology. These are shown in the top fraction of the stacked bars. In contrast, the sales of new machines shown in the bottom part of the stacked bars was modest.

Figure 28: Dobson & Barlow orders for Indian-cotton related machinery types

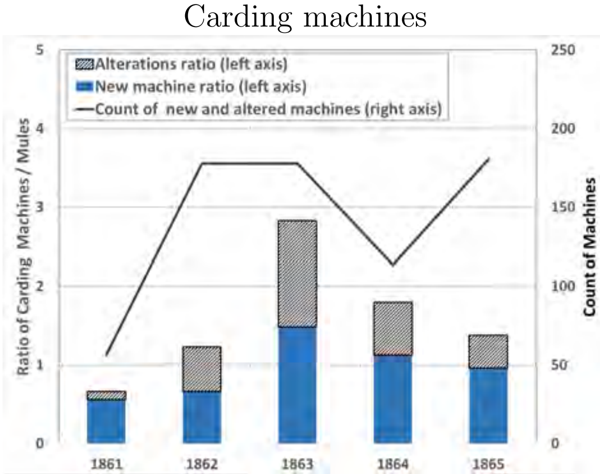
Gin orders



Openers/scutchers



Carding machines

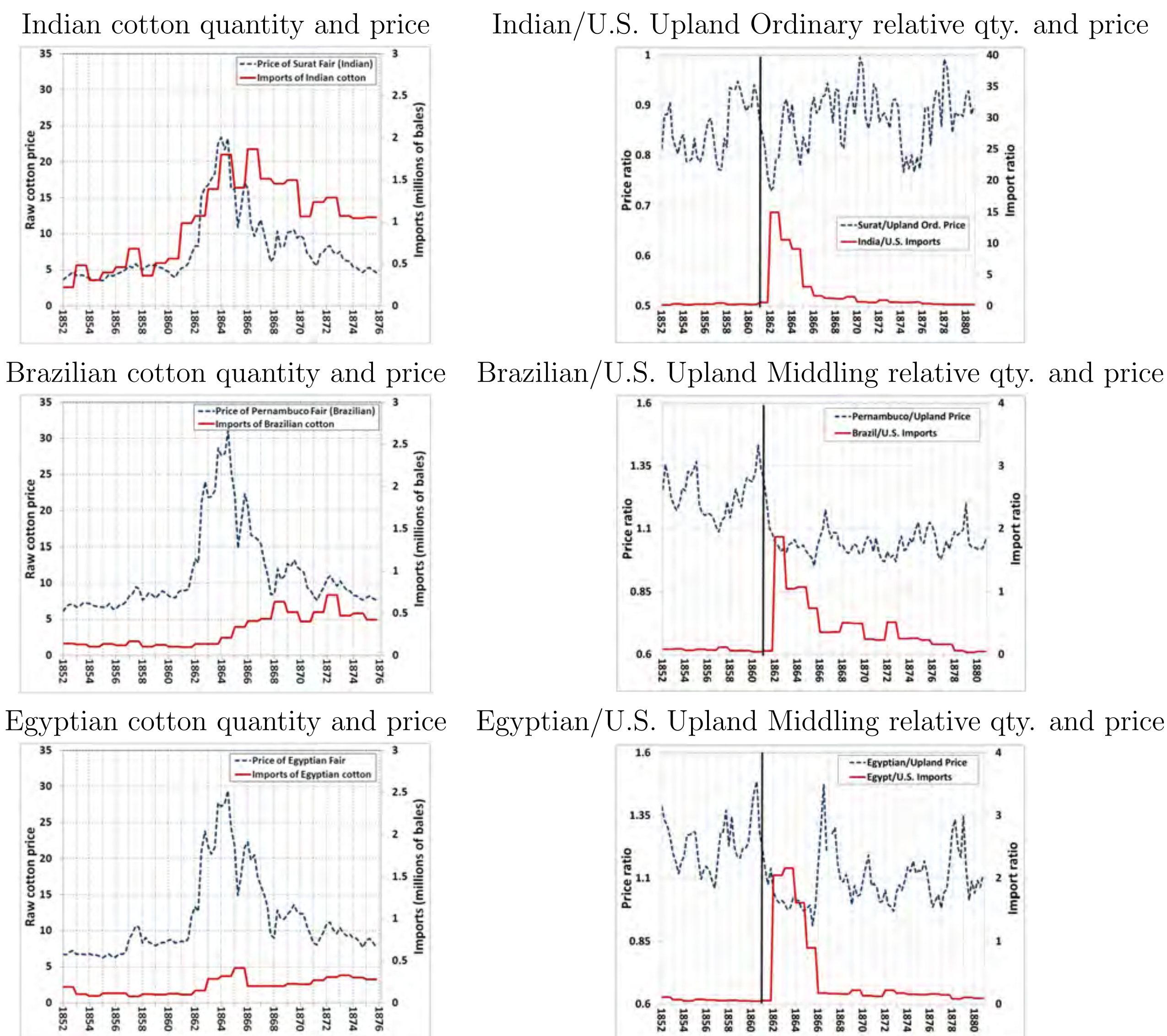


Data from Dobson & Barlow contract books accessed at the Lancashire County Archives. Openers/scutchers includes lap machines. Carding includes both finishing cards and breaking cards. The date is based on when the contract was received.

A.4 Appendix to the price analysis

Figure 29 providing some additional graphs describing the movements of the actual and relative prices and actual and relative quantities of the various cotton varieties.

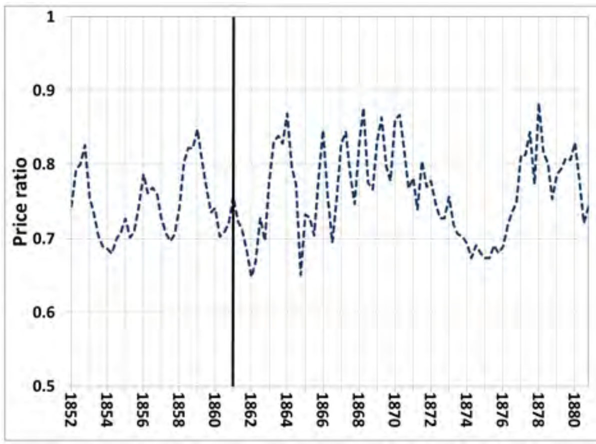
Figure 29: Prices and quantities for Indian, Brazilian, and Egyptian cotton



Price data gathered from *The Economist* magazine. Quantity data from Ellison (1886). For prices the denominator is the closest U.S. variety, while for quantities the denominator is total imports of cotton from the U.S.

Figure 9 in the text describes the movement of the relative price of Indian to lower-quality U.S. cotton (Upland Ordinary). The chart below shows that essentially the same pattern holds when Indian cotton is compared instead to a higher quality grade of U.S. cotton, Upland Middling.

Figure 30: Ratio of Indian / higher-quality U.S. cotton (Upland Middling)



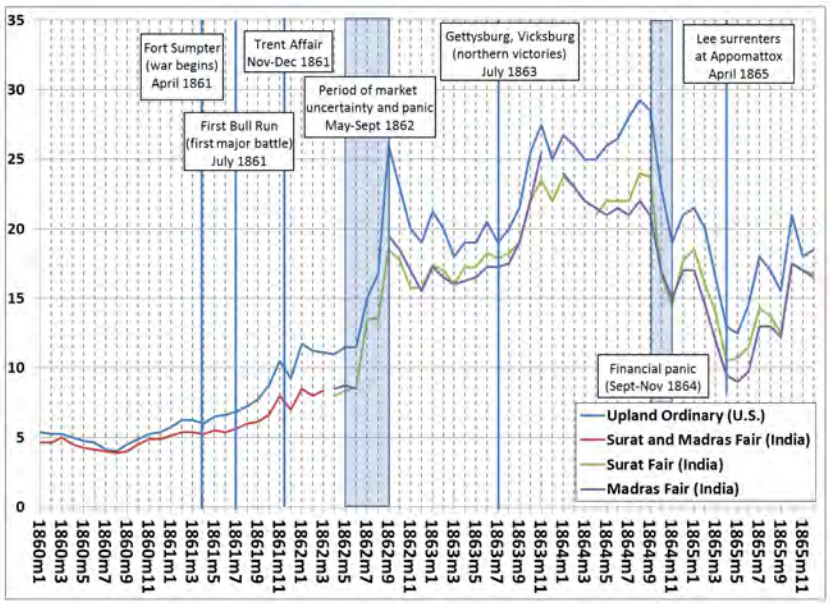
Data from The Economist.

To explore the timing of these patterns in greater depth, I turn to monthly data over the 1860-1865 period. The upper panel of Figure 31 shows the prices of U.S. and Indian cotton, in levels. The lower panel shows relative prices. Key events have been marked on both charts. We can see that price rose slowly following the onset of the Civil War, while relative pries experienced a consistent decline throughout 1861 and into 1862. This was followed by a period of market panic lasting from May to September of 1862, characterized by an extraordinarily rapid rise in prices.[52] During this period, the relative price experienced a sharp rise and fall, as the price of Indian cotton followed U.S. cotton prices upward with some delay. We can see from the bottom panel that it was not until the end of 1862, over a year and a half into the war, that relative prices began a sustained increase. By mid-1863, relative prices had returned to the historically high levels of 1860. A downward adjustment followed the Northern victories in July 1863, which ensured that the war would drag on, but relative prices remained near their pre-war average through the end of 1865, with the exception of the short-lived drop during by the financial panic of September-November of 1864. Finally, the last months of the war in the Spring of 1865 saw a sharp drop in prices, but notably, relative prices moved very little during this period.

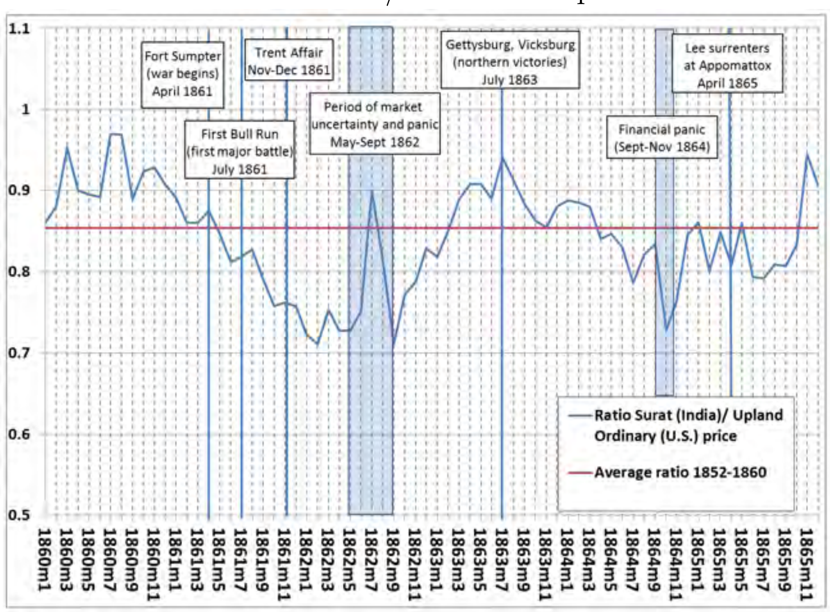
[52]This panic sparked, in part, by a speech by Lord John Russell in June of 1862 confirming Britain's intention to stay out of the conflict and was ended by Napoleon III's offer to mediate between the sides in October of 1862.

Figure 31: Monthly prices during the 1860-1865 period

Prices of U.S. and Indian cotton



Ratio of Indian/ U.S. cotton prices



Price data gathered from *The Economist* magazine.

A.4.1 Full price regression results

The tables below presents the full set of regression results (excluding fixed-effects) corresponding to Figures 10 and 11 in the main text. For the first set of results, the specification is:

$$\log(RP_{jt}) = \alpha + \Big[\sum_{k=1859}^{1875} \gamma_k \times YR_k \times INDIA_j \Big] + \Psi_j + \xi_t + Q_t + \epsilon_{jt}$$

These results correspond to Figure 10.

For the second set of results, which correspond to Figure 11 in the main text, the specification is:

$$\log(RP_t^{INDIA/US}) = \alpha + \Big[\sum_{k=1859}^{1875} \gamma_k \times YR_k \Big] + \epsilon_t \,.$$

Table 8: Full regression results for Figure 10

	Without controlling for the Indian Rebellion of 1858	With a dummy control for the Indian Rebellion of 1858
india_1859	0.0623*	0.00164
	(0.0336)	(0.0339)
india_1860	-0.0731***	-0.0630***
	(0.0236)	(0.0242)
india_1861	0.0451	0.0552
	(0.0337)	(0.0346)
india_1862	0.121***	0.131***
	(0.0244)	(0.0256)
india_1863	0.248***	0.258***
	(0.0302)	(0.0312)
india_1864	0.206***	0.216***
	(0.0306)	(0.0316)
india_1865	0.239***	0.249***
	(0.0264)	(0.0275)
india_1866	0.0851	0.0953
	(0.0601)	(0.0607)
india_1867	0.154***	0.164***
	(0.0498)	(0.0504)
india_1868	0.203***	0.213***
	(0.0306)	(0.0315)
india_1869	0.258***	0.269***
	(0.0192)	(0.0207)
india_1870	0.243***	0.253***
	(0.0292)	(0.0302)
india_1871	0.260***	0.271***
	(0.0238)	(0.0250)
india_1872	0.260***	0.270***
	(0.0197)	(0.0211)
india_1873	0.225***	0.235***
	(0.0198)	(0.0212)
india_1874	0.0619***	0.0720***
	(0.0234)	(0.0247)
india_1875	0.0587**	0.0688***
	(0.0230)	(0.0243)
mutiny		0.0708**
		(0.0274)
Constant	1.271***	1.275***
	(0.0206)	(0.0188)
Observations	288	288

This table presents regression specifications generated using the specification in Equation 3. Newey-West standard errors calculated using a lag length of eight are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Full regression results for Figure 11

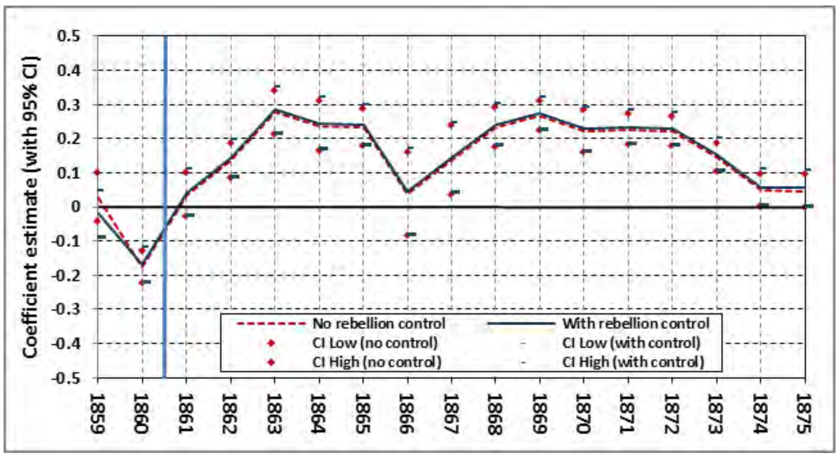
	Without controlling for the Indian Rebellion of 1858	With a dummy control for the Indian Rebellion of 1858
india_1859	0.0825***	0.0143
	(0.0136)	(0.0161)
india_1860	0.0779***	0.0893***
	(0.0149)	(0.0112)
india_1861	-0.0146	-0.00325
	(0.0189)	(0.0173)
india_1862	-0.0733***	-0.0619***
	(0.0161)	(0.0142)
india_1863	0.0467***	0.0581***
	(0.0137)	(0.0112)
india_1864	-0.00246	0.00891
	(0.0198)	(0.0182)
india_1865	0.00164	0.0130
	(0.0148)	(0.0126)
india_1866	0.0666***	0.0780***
	(0.0130)	(0.0104)
india_1867	0.0756***	0.0870***
	(0.0152)	(0.0131)
india_1868	0.0389*	0.0503**
	(0.0223)	(0.0210)
india_1869	0.0668***	0.0782***
	(0.0132)	(0.0107)
india_1870	0.109***	0.120***
	(0.0162)	(0.0142)
india_1871	0.0642***	0.0756***
	(0.0175)	(0.0157)
india_1872	0.0392***	0.0506***
	(0.0128)	(0.0101)
india_1873	0.0578***	0.0691***
	(0.0140)	(0.0117)
india_1874	-0.0456***	-0.0342***
	(0.0137)	(0.0113)
india_1875	-0.0515***	-0.0402***
	(0.0130)	(0.0104)
mutiny		0.0796***
		(0.0170)
Constant	0.835***	0.824***
	(0.0127)	(0.0101)
Observations	96	96

This table presents regression specifications generated using the specification in Equation 4. Newey-West standard errors calculated using a lag length of eight are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.4.2 Using the same denominator for all relative price series

In the results in Figure 10, I compared cotton from India, Brazil, and Egypt to the closest quality U.S. variety for each. The motivation is that each variety should be compared to the most similar U.S. variety. However, we may be worried that using a different denominator in these relative prices is influencing the results. To address this concern, I have generated additional results where each alternative variety is compared to the same U.S. benchmark price (Upland Middling), which was the most import benchmark out of all cotton prices during this period. The results are shown below. Comparing this to the results in the main text, it is clear that this change makes little difference to the results.

Figure 32: Behavior of the Indian/U.S. cotton price relative to the pre-war period comparing each alternative variety to the U.S. Upland Middling price



Estimated coefficients and 95% confidence intervals generated using quarterly data from 1852-1875. Regressions use Newey-West standard errors with a lag length of eight. Regressions are done with and without controlling for the Indian Rebellion of 1858 using an indicator variable for 1858-59.

A.5 Some evidence on the elasticity of substitution between cotton types

This appendix provides some estimates of the elasticity of substitution between Indian and U.S. cotton in the context of the motivating theory. In this context, the elasticity of substitution can be estimated by looking at the impact of short-run changes in relative supplies on relative prices. The estimation equation is,

$$\log(c_{I,t}/c_{US,t}) = \beta_0 + \beta_1 \log(Z_{I,t}/Z_{US,t}) + \beta_2 TT_t + \epsilon_t \ ,$$

and the elasticity of substitution is $\sigma_l = -1/\beta_1$. In any regression of relative prices on relative quantities we must be worried about bias due to reverse causality, though this is less of a concern in the current agricultural setting, where any response of quantities to prices would likely have been lagged by at least one year. However, I still address this concern by using an instrumental variable that directly affects relative input supplies in period t but is not otherwise related to relative prices. To satisfy the exclusion restriction, the instrumental variable must be exogenous and vary only in the short-run, so that it does not affect relative technology levels.[53] This approach allows me to estimate the elasticity of substitution between Indian and U.S. cotton, but unfortunately it is not possible to do the same for Brazilian or Egyptian cotton.[54]

The instrument that I exploit is variation in the length of the cotton growing season in the U.S. These data data were collected from the New York Times (Oct. 8, 1866) and cover 1837-1860.[55] The first bloom and first frost dates played an important role in determining the size of the U.S. cotton crop, which in turn had a large effect of world prices.[56] The growing season length is the number of days between first bloom and first frost. Because these weather events represent exogenous short-run fluctuations, they should satisfy the exclusion restrictions. The length of the growing season does not exhibit a trend over time nor is there any evidence of autocorrelation. The two first-stage regressions are,

$$\log(Z_{I,t}/Z_{US,t}) = \alpha_0 + \alpha_1 GROWINGDAYS_t + \alpha_2 TT_t + e_t \ ,$$

$$\log(Z_{I,t}/Z_{US,t}) = \alpha_0 + \alpha_1 BLOOM_t + \alpha_2 FROST_t + \alpha_3 TT_t + e_t \ ,$$

where $GROWINGDAYS_t$ is the length of the growing season, $BLOOM_t$ is the number of days in the year before the first bloom, and $FROST_t$ is the number of days in the year before the first killing frost.

Regression results are shown in Table 10 for Indian/U.S. cotton. Because these are time series regressions, I use Newey-West standard errors with a lag length of 2 in order to allow for some serial correlation across observations. Column 1 shows the relationship between relative quantities and relative prices estimated using OLS. In columns 2-3, the length of the growing season (bloom to frost) is used as an instrument for relative quantities, while in columns 4-5 I use the bloom date and frost date separately.

The first-stage regression results in Table 10 indicate that the weather variables are providing a strong instrument for the relative supply of Indian to U.S. cotton. These variables take the expected sign; a longer growing season, an earlier bloom date, or a later frost date in the U.S. decrease the ratio of Indian to U.S. cotton. In

[53] I.e., fluctuations in the instrument should not affect the balanced growth path, which could generate directed technical change which would bias the resulting elasticity estimates.

[54] The instruments do not perform well for the relative quantity of Brazilian to U.S. cotton, most likely because the Southern U.S. and Northern Brazil were subject to correlated weather shocks. For Egypt, sufficient price and quantity data are not available.

[55] I am grateful to Claudia Steinwender for making me aware of these data.

[56] Writing in a somewhat later period, Garside (1935) (p. 15) notes that "It has been calculated that climatic conditions, which of course are uncontrollable, account for about 50 percent of the total factors affecting yield per acre."

the top panel of Table 10 we see that there is always a negative relationship between relative quantities and relative prices, as expected between two inputs which are imperfect substitutes. However, the point estimates are also small, suggesting that relative prices did not respond strongly to changes in relative quantities, consistent with inputs that were reasonably substitutable. The resulting elasticity estimates derived from these results are shown at the bottom of the table. In all cases, these estimates suggest that the elasticity of substitution between Indian and U.S. cotton was above two.

Table 10: Estimated elasticity of substitution between Indian and U.S. cotton

	Dependent Variable: Relative cotton prices				
	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Relative	-0.0124	-0.0779	-0.0731	-0.0182	-0.0555
quantity	(0.0235)	(0.0500)	(0.0478)	(0.0438)	(0.0467)
Time-trend			0.00363*		0.00320*
			(0.00187)		(0.00181)
Constant	-0.315***	-0.423***	-0.461***	-0.325***	-0.426***
	(0.0355)	(0.0783)	(0.0894)	(0.0668)	(0.0860)
Observations	24	24	24	24	24
	First-stage regression results				
Growing days		-0.011**	-0.011**		
		(0.003)	(0.002)		
Bloom date				0.021***	0.0156***
				(0.005)	(0.005)
Frost date				-0.006	-0.009**
				(0.004)	(0.004)
Time trend			0.026***		0.021**
			(0.007)		(0.008)
Constant		-0.077	-0.346	-3.009**	-1.657
		(0.452)	(0.359)	(1.352)	(1.452)
F-statistic		12.70	25.09	10.99	12.40
	Implied elasticity of substitution				
Main estimate	80.65	12.84	13.69	54.97	18.02
95% C.I.	(16.37, $+\infty$)	(5.51, $+\infty$)	(5.80, $+\infty$)	(9.18, $+\infty$)	(6.55, $+\infty$)

Regressions use annual data from 1837 to 1860. Data from Ellison (1886). Standard errors are Newey-West with a lag length of two, include a small-sample correction, and are robust to arbitrary heteroskedasticity.

An alternative approach to estimating the elasticity of substitution, taken by Irwin (2003), is to use the Almost Ideal Demand System (AIDS) introduced by Deaton & Muellbauer (1980). The advantage of the AIDS approach is that it allows for a more flexible demand system than the CES model I use, with cross-price effects. One disadvantage is that it requires strong assumptions about the elasticity of supply of inputs, which will bias the AIDS estimates downwards. Another potential issue with this approach is that it does not attempt to control for the influence of directed technical change, which will bias the AIDS estimates upwards. The estimating equation for the AIDS approach is,

$$w_{it} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ \ln(c_{jt}) + \beta_i \ \ln(D_t/C_t) + u_t$$

where w_{it} is the expenditure share of input type i, c_{jt} is the price of input j, D_t is total expenditure on all inputs, C_t is a price index over all inputs, and u_t is a disturbance term. For empirical applications, the input price index is generally approximated by,

$$ln(C_t) = \sum_{k=1}^{n} w_{kt} \ \ln(c_{kt}) \ .$$

Given the estimated coefficients from these equations, the elasticity of substitution between any two input types can be calculated according to $\sigma_{ij} = 1+\gamma_{ij}/(w_i w_j)$, where the corresponding standard error is the estimated standard error for γ_{ij} divided by $w_i w_j$.

Estimating these equations requires the prices and import quantities for each input variety on the British market. Separate import quantity data are not available for higher and lower-quality U.S. cotton, so I am able to calculate only an overall elasticity of substitution between each alternative variety and all U.S. cotton. Following Irwin (2003), I estimate these equations using seemingly unrelated regressions while imposing symmetry ($\gamma_{ij} = \gamma_{ji}$). In estimating these equations it is necessary to drop one, so I drop the equation for Egyptian cotton, the fourth largest variety.

Table 11 presents a summary of the elasticity of substitution estimates generated using the AIDS approach for a variety of data sources and time periods. The first column of Table 11 reproduces results found in Irwin (2003) using data from Mann (1860). The remaining columns present new estimates generated using data from Ellison (1886) for a variety of time periods. The most relevant are in Columns 2, which present results for the twenty-year period just before the war. Column 3 presents results for the twenty years after the war. Both of these suggest that the elasticity of substitution between U.S. and Indian cotton was above 1 and likely also above 2. The elasticity of substitution between U.S. and Brazilian cotton also appears to be above 1, and some specifications generate point estimates that are above 2. There is little evidence of substitution between Indian and Brazilian cotton.

Table 11: Elasticity of substitution estimates generated using the AIDS approach

	Irwin (2001)	Additional estimates			
Data source:	Mann	Ellison	Ellison	Ellison	Ellison
Years:	1820-1859	1840-1859	1865-1884	1820-1859	1820-1884
U.S.-India	1.96	2.19	2.38	1.58	1.32
	(0.80)	(1.26)	(0.97)	(1.28)	(1.14)
U.S.-Brazil	3.88	2.95	1.66	4.16	5.39
	(0.70)	(0.73)	(3.06)	(0.70)	(1.27)
India-Brazil		-0.97	0.24	-0.01	-0.79
		(4.02)	(4.83)	(3.85)	(4.50)

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Symmetry is imposed in all regressions, so for example, the coefficient on U.S. cotton in the Brazilian cotton regression must equal the coefficient on Brazilian cotton in the U.S. cotton regression. Durbin-Watson test do not show evidence of serial correlation in the Indian cotton regressions using either the Mann data or the Ellison data from before the war (columns 1-2 and 4). There is evidence of serial correlation in the Indian cotton regressions that include post-1860 data (columns 3 and 5), which may be related to the persistent effects of the shock.