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

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Abstract

The leading theory of directed technical change, developed by Acemoglu (2002), offers two main predictions. First, when inputs are sufficiently substitutable, a change in relative input supplies will generate technical change that augments inputs which become relatively more abundant. Second, if this effect is sufficiently strong, the relative price of the relatively more abundant inputs will increase – the strong induced-bias hypothesis. This paper provides the first empirical test of these predictions using the shock to the British cotton textile industry caused by the U.S. Civil War (1861-1865). Using detailed new patent data, I show that the shock increased innovation in Britain directed towards taking advantage of Indian cotton, which had became relatively more abundant. The relative price of Indian cotton first declined and then rebounded, consistent with strong induced-bias. Given my elasticity of substitution estimates, these findings are consistent with the predictions of the theory.

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

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1 Introduction

The idea that a change in the availability or price of inputs to production can play an important role in influencing the rate and direction of technical progress has been used to explain a diverse set of economic phenomena.[1] To cite one example, it has been suggested that the increase in skilled workers in the U.S. in the 1970s caused skill-biased *directed technical change*, and that this directed technical change allowed the skill premium to increase in spite of the increase in the relative abundance of skilled workers (Acemoglu (1998), Kiley (1999)). This example highlights two relationships which will be the focus of this paper. First, that a change in the relative supply of inputs can cause innovation to be directed towards technologies which augment either one or the other of the inputs. Second, that in some cases directed technical change can generate a positive long-run relationship between the relative quantity of inputs to production and the relative price of those inputs.

These ideas have been formalized by by Acemoglu (2002, 2007), building on previous work by Hicks (1932) and others.[2] Acemoglu shows that the direction of technical change depends crucially on the elasticity of substitution between inputs, represented by σ. When this elasticity is low ($\sigma < 1$), technical change will be directed towards technologies that augment the input which has become relatively scarce. In contrast, when the elasticity of substitution between inputs is high ($\sigma > 1$), technical change will be directed towards technologies that augment the input which has become relatively more abundant. Next, he shows that, when the elasticity of substitution between inputs is sufficiently high ($\sigma > 2$), technical change will be so strongly directed towards technologies that augment the more abundant input that the relative price of that input can increase. This *strong induced-bias hypothesis* may explain, for

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[1] In economic history, it has been suggested that a shortage of labor drove the development of labor-saving innovations which played an important role in industrialization in Britain and the U.S. (Habakkuk (1962), Allen (2009)). In the environmental literature, it has been pointed out that the impact of regulations that change the price of inputs, such as a carbon tax, will depend crucially on whether these changes generate directed technical change, and on the direction that this innovation takes (Acemoglu *et al.* (2012)). Related papers in the environmental literature include Porter (1991), Lanjouw & Mody (1996) and Jaffe & Palmer (1997). The idea of directed technical change has also been applied to consider the impact of high energy prices (Newell *et al.* (1999), Popp (2002)), the causes of cross-country productivity differences (Acemoglu & Zilibotti (2001), Caselli & Coleman (2006)), and agricultural productivity trends (Hayami & Ruttan (1970), Olmstead & Rhode (1993)).

[2] Other important contributions to this literature include Kennedy (1964), Samuelson (1965) and Drandakis & Phelps (1966).

example, how an increase in the supply of skilled workers may increase the skill wage premium.

The aim of this paper is to test these predictions. To do so, I consider a large exogenous shock 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, which provided most of the raw cotton imported into Britain prior to the war (77% in 1860). This forced British producers to turn to raw cotton from alternative suppliers, such as India, Brazil, and Egypt. In response to the resulting high prices, all of these alternative suppliers, led by India, substantially increased their exports to Britain. However, the cotton available from these alternative suppliers differed from American cotton in important ways. This was particularly true for cotton from India, the second largest supplier, which was a low-quality variety that was difficult to clean and prepare.

Contemporary observers noticed the important changes in the cotton textile industry that were generated by the increased importance of Indian cotton during the Civil War period. In his book, *The Cotton Trade in Great Britain*, 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." Historian of the industry have also remarked on the changes that took place in the production process during this period. D.A. Farnie, in his authoritative history of the British cotton textile industry in the 19th century (Farnie (1979) (p. 152-153)), writes, "The shortage of American 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..."

The first contribution of this paper is to track the nature of these technological changes in a rigorous way. In order to identify the direction of technological change, I gathered new data on British patents containing a high level of detail on the types of new technologies being created. Using these patent data it is possible to track patterns of innovation in particular types of cotton textile machines. Because some of these machines – such as gins, openers, and scutchers – were particularly important for using Indian cotton, these data can be used to identify the impact of the change in input supplies on the direction of technological progress. The patent data show that there was a substantial increase in cotton-textile related innovation during the Civil War period and that this increase was concentrated in those machines that were particularly important for using Indian cotton. This increase peaked two to four years into the war, a time-frame that is consistent with qualitative evidence on the lag needed to produce new technologies such as cotton gins. The same features appear when I focus only on high-quality patents, using three measures of patent quality. Thus, I find that the shock generated directed technical change towards the input which had become relatively more abundant, Indian cotton.

The second contribution of this paper is to track the impact on relative prices in order to test the strong induced-bias hypothesis. To do so, I use new data on the prices of these cotton varieties gathered from The Economist magazine. In the absence of directed technical change, the price of alternative cotton varieties, relative to U.S. cotton, should have fallen as they became relatively more abundant. On the other hand, the technical change directed towards augmenting Indian cotton may offset this, by increasing the demand for that variety. Graphing the relative price of Indian to U.S. cotton, I observe that there was a decrease in the relative price of Indian to U.S. cotton in the first two years of the Civil War, followed by a rebound starting in 1863, around the time when the new technologies were becoming available. Despite remaining relatively abundant after 1863, compared to the pre-war period, the relative price of Indian cotton was at or above the level achieved in the pre-war period, a pattern that is consistent with the strong-induced bias hypothesis. To strengthen this result, I compare this pattern econometrically to that observed for Brazilian cotton, a smaller alternative variety for which I observe no evidence of directed technical change. This allows me to control for other time-varying factors that may be affecting relative prices.

To relate these findings to the theory, I estimate the elasticity of substitution between Indian and U.S. cotton. Once I have this elasticity parameter, I know the predictions of the theory and can compare them to my empirical results in order to test the theory. To estimate this elasticity, I use is the average date of the first bloom and first freeze in the U.S. South from 1837-1860, which determine the length of the growing season and thus the size of the U.S. crop, as an instrument for the relative supply of Indian to U.S. cotton. The resulting estimates suggest an elasticity of substitution between U.S. and Indian cotton that was above two. Given that elasticity, the predictions of the theory regarding both the direction of technological progress and the behavior of relative prices match my empirical findings.

This empirical setting has a number of features which are important for my study. First, the impact of the Civil War on the cotton textile industry was large and lasted for several years. There is evidence that output in the industry dropped by as much as 50%. Hundreds of thousands of mill operatives found themselves out of work or working short-time. Thus, this event was large enough to influence innovation rates. Second, I can compare outcomes in the the cotton textile industry to other similar textile industries – based on wool, linen, and silk – which were also important in Britain during this time, but which were not negatively impacted by the Civil War.[3] This will help me control for other time-varying factors that may be affecting innovation rates. Third, despite the magnitude of the shock, there was virtually no government intervention. This was primarily due to the strong free-market ideology which was dominant in Britain at this time. This reduces the chance that the effects I observe were influenced by government interference.

Several previous empirical studies have also looked at the relationship between input supplies (or prices) and the direction of technological progress (Newell *et al.* (1999), Popp (2002), Acemoglu & Finkelstein (2008), Aghion *et al.* (2010)).[4] One

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[3] If anything, these industries benefited somewhat from the reduction in competition from cotton textiles.

[4] An alternative approach 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. In particular, he finds that changes in relative factor endowments are negatively correlated with relative factor prices, and that this correlation is larger for factor prices in the long run, which he interprets as evidence of technical change biased toward the factor which became relatively scarce. This approach is potentially complementary to microeconomic studies such as my paper. However, standing alone it is difficult to be sure that the changes he observes are truly due to directed technical change rather than other factors, since technology is not observed, and controlling for other potential explanations is difficult in a cross-country context. While my 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 (2003) 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.* (2009) 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.

feature that distinguishes this paper from these existing studies is that I observe the prices and quantities of multiple inputs into the production process. This means that I can estimate the elasticity of substitution between these inputs, derive the predictions of the theory, and compare these predictions to what I observe in the data. That has not been done previously. Also, existing studies use input prices as their main explanatory variable, which means that they are unable to look at the impact of a change in relative quantities on relative input prices. Thus, this is the first study to investigate the strong-induced bias hypothesis. Another important difference is that this study uses a large exogenous shock to provide causal evidence in a cleaner way than was previously possible. A final difference is that my empirical setting is largely free of government intervention, which may be a concern in other settings.

The next section describes the empirical setting while Section 3 presents a directed technical change model adapted to this setting. The data are described in Section 4. I analyze the impact on innovation patterns using the patent data in Section 5. The impact on input prices is analyzed in Section 6. In Section 7, I estimate the elasticity of substitution parameters that determine the predictions of the theory and compare these predictions to my empirical results in order to evaluate the theory. Section 8 concludes.

2 Empirical setting

2.1 The Cotton Textile Industry

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] For example, in 1860 cotton textile exports were valued at £52 million, dwarfing the next largest export categories, wool textile exports at £15.7 million and iron and steel at £13.6 million.[6]

The production of cotton textiles can be divided into four steps: Preparation,

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

[6] Data from Mitchell & Deane (1962).

Spinning, Weaving, and Finishing. Preparation 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] 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. Textile technologies made up over 11% of all British patents during 1855-1883, a time at which Britain was a world technology leader.

2.2 Other textile industries

Textile industries based on wool, linen, and silk were also important in Britain during the period I study. Of these, wool was by far the largest. Technologically, these industries were similar to the cotton textile industry. Spinning and weaving machinery originally developed in the cotton textile industry was often later adapted to work with other textile inputs. One indicator of this similarity is that it is common to find textile technology patents that mention that they may be used with more than one type of input. Geographically, these industries were concentrated in Northern England near the cotton textile industry. They were also subject to many of the same demand shocks experienced by the cotton textile industry and acted as substitutes for cotton textiles to a limited extent. However, as I will discuss, these industries were not negatively affected by the Civil War shock. As a result, these similar industries should provide a good control group for comparison with the cotton textiles industry.

2.3 The impact of the U.S. Civil War

The British cotton textile industry was entirely dependent on imported raw cotton, as growing cotton in Britain was infeasible. After the beginning of the U.S. Civil War in April of 1861 the North almost immediately declared a naval blockade of Southern ports. While initially ineffective, the blockade became increasingly disruptive to

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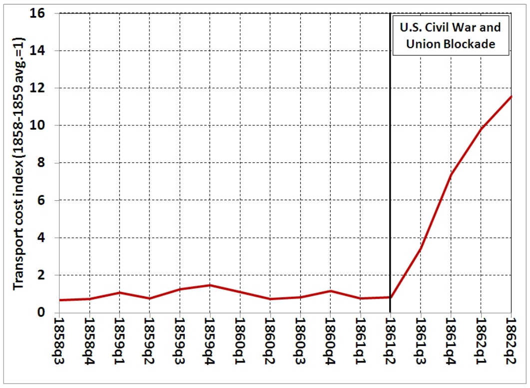
[7] Definitions of these and other textile-related terms are available in Appendix A.1.2. The first stage of the preparatory process, ginning, generally took place in the cotton producing region, while later stages, such as opening and carding, generally took place in manufacturing centers such as Britain.

Southern commerce, including the export of raw cotton, as the war continued and the Union Navy expanded. Figure 1 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 1: 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.

Not surprisingly, such a large increase in transport costs had a significant affect on British imports. At the beginning of the study period, the cotton textile industry was heavily dependent on cotton growers in the U.S. South, as is evident in the left-hand panel of Figure 2. Other suppliers, particularly India, but also Egypt and Brazil, 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. 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.[8]

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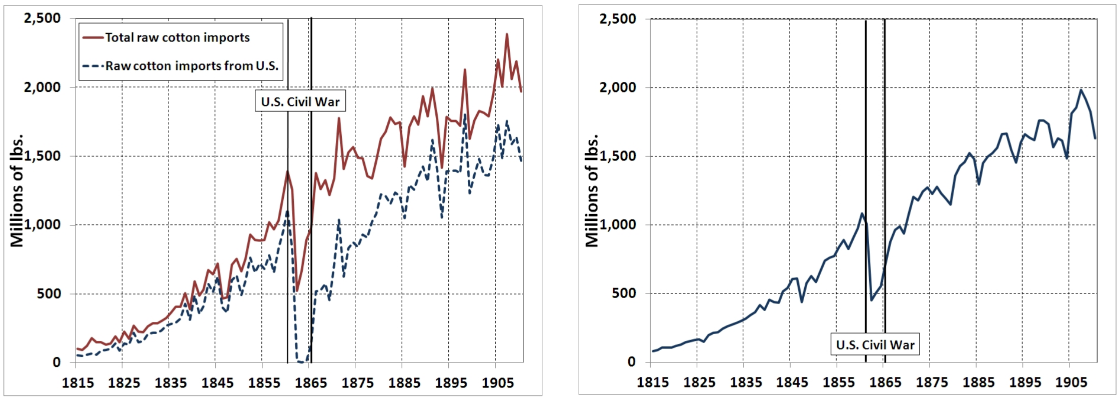
[8] It is reasonable to think of the amount of cotton required for a given amount of cotton textiles as being largely fixed, though, or course, small savings could be made. The reduction in production also led to massive unemployment in the cotton textile districts, resulting in the “Lancashire Cotton 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.

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


British cotton imports

British domestic cotton consumption

Data from Mitchell & Deane (1962).

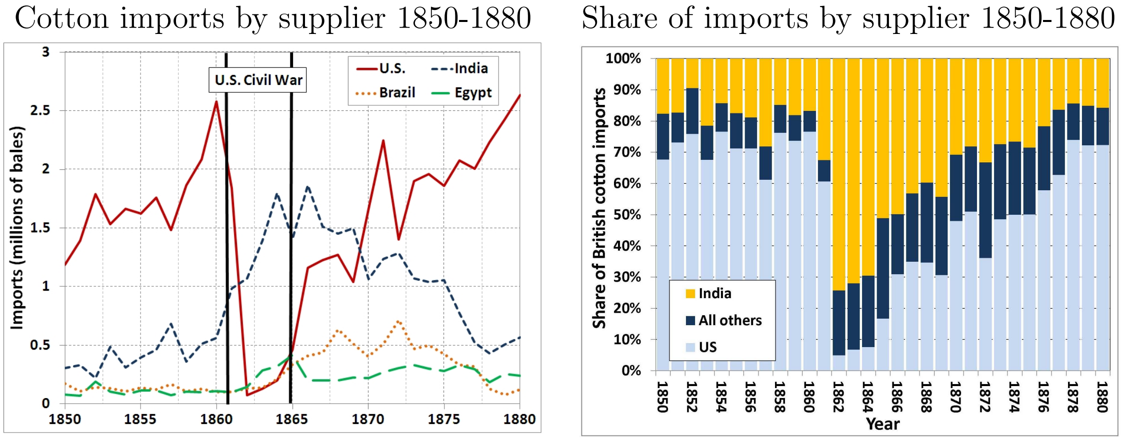
Figure 3 shows the impact on the level of imports from each major supplier (left panel), and the share of total imports from the U.S., India, and other suppliers (right panel).[9] It is clear that the shock caused a sharp drop in imports from the U.S. and an increase in imports from other suppliers, particularly India. 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.[10]

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.

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

[10] 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.

Figure 3: British cotton imports and share of imports by supplier 1850-1880


Cotton imports by supplier 1850-1880

Share of imports by supplier 1850-1880

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 1870's. 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.[11] The shock was largely transmitted through the cotton textile industry, rather than being a broad-based economic shock.[12] The other textile industries – wool, linen, and silk – showed no negative effects during the Civil War. If anything, these sectors benefited from the reduced competition from cotton textiles.

The theory offered in the next section will focus on the response of technology and prices to a permanent change in the relative supply of inputs. Thus, it is particularly important to understand how the war affected agents' expectations of the

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[11] See figures in Appendix A.1.7.

[12] See Appendix A.1.7. Once raw cotton imports are removed, total British imports do not appear to be affected during the shock period. Similarly, once textile exports are excluded, British manufacturing exports also fail to show any large effect from the shock.

long-run level of relative input supplies. 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 people believed that the war, though temporary, would cause a long-term shift in relative supplies.[13] Thus, it is reasonable to think of the war as shifting, for at least some time, agents' expectations of the long-run growth path of the economy.

2.4 Differences between cotton types

Just prior to the war in 1860, the U.S. South was supplying 77% of British imports (by quantity), India supplied 17%, Brazil and Egypt each supplied around 3%, and smaller amounts also came from other sources. But there were important differences between these varieties. Indian cotton was a low-quality variety that competed primarily with the lower grades of U.S. cotton, both of which were used to produce lower-quality goods. Brazil and Egypt produced high-quality cotton that competed with the better grades produced by the U.S. These varieties were used to produce higher-quality goods.

The differences between the two largest varieties, U.S. and Indian cotton, are particularly important. The raw cotton supplied by the U.S. and India at the time of this study came from biologically distinct varieties. The cotton available from India in the 1860s was widely considered to be inferior to U.S. cotton in several important ways, a fact which was reflected in the lower price per pound paid for Indian cotton throughout the period I study (see Figure 8 in Section 6).

One difference between these varieties was that Indian cotton was more difficult to

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[13] To cite one example, near the beginning of the war, The Economist (May 18, 1861) writes, "We hope that there is still no reason to apprehend a sudden break up of the industrial organization at the south, which would be a greater present evil than slavery itself, great as that is; we hope there is no probability of a servile war, which is but another name for the same calamity...and, except for causes such as these, we do not apprehend any danger to the cotton crop...Still when such a calamity is within the range of discussion, it is fitting to have the last material facts on the subject present to our minds." A year and a half later, 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..."

prepare for spinning. In particular, it was difficult to remove the seeds from the Indian cotton using the cotton gins which were available. This was a result of the unusually small size of the Indian cotton seeds, as well as their strong bond to the cotton plant (see, e.g., 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.[14] However, American saw gins tended to cut up the Indian cotton fibers, reducing their length, and therefore their usefulness.[15] In addition, the saw gins were much more complicated and expensive. For these reasons the saw gin proved ill suited for India. In addition to the difficulty in removing seeds, Indian cotton fibers were also more difficult to open, a process which was done using openers.

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.[16] 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.[17] The fact that Indian cotton was shorter likely compounded the difficulties involved in ginning, since using a gin could significantly shorten the fiber length.[18]

The difficulty that British producers faced in using Indian cotton is reflected in the share of cotton wasted in the production process, plotted in Figure 4. This graph shows that there was a sharp increase in cotton waste corresponding to the switch to Indian cotton in 1862. This is particularly striking given that price of raw cotton was

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[14] Illustrations of both machines are available in Appendix A.1.3.

[15] See example in Appendix A.1.5.

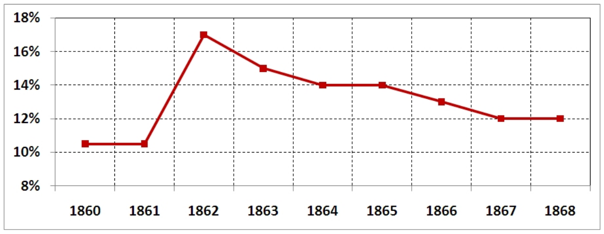
[16] See, e.g., the description in Wheeler (1862) (p. 125-129) and Mackay (1853).

[17] Appendix A.1.4 shows a comparison of fiber lengths from several of the varieties of cotton available to British producers. The Indian varieties are shorter than all other varieties.

[18] This is illustrated in Appendix A.1.5, which shows the difference between the length of fiber obtained after hand-cleaning and mechanically ginning using a sample of Brazilian cotton.

very high by 1862, which must have induced producers to take measures to limit such waste. The slow reduction in the waste level after 1862 may indicate improvements in the ability of textile manufacturers to use Indian cotton efficiently.

Figure 4: Share of waste in total raw cotton input 1860-1868



Data from Forwood (1870). These values are calculated by taking the weight of cotton consumed and subtracting the weight of yarn produced, to obtain the weight wasted in the production process.

Another indicator of the differences between U.S. and Indian cotton can be found in the patent descriptions themselves. Though most patents provide only a simple description of the mechanisms involved, a few also mention the motivation behind the new technology. One example is Patent No. 2162 from 1862, which describes a patent filed in Britain in 1862 which was specifically designed to open the more tightly compressed East Indian cotton.[19]

2.5 How long to invent new technologies?

Because this studies relies, in part, on the timing of the Civil War for identification, it is important to consider the lag that we should expect between an increase in the incentives for innovation and the production of patentable new technology designs. It is very difficult to address this concern rigorously, since the lag is likely to vary across technology types and individual inventors and the moment at which an inventor begins work on a problem is generally unobserved. However, historical evidence can provide some guide.

One piece of evidence that is particularly relevant for this study is provided by Lakwete (2003) in her authoritative history, *Inventing the Cotton Gin*. This account

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[19] This patent was classified in the spinning technology category and the "Openers & Scutchers, etc." subcategory, and also has "cotton" in the patent title, leading it to be identified as a cotton-related patent. A description of this patent is available in Appendix A.1.6.

details numerous instances in which inventors produced new innovations or patentable improvements 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 McCarthy'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.

3 Theory

This section adapts the theory of Acemoglu (2002) to the empirical setting that I investigate. The main challenge in doing so is that the cotton textile industry uses multiple types of raw cotton inputs and the elasticity of substitution may vary across different input pairs. In order to accommodate this feature, I divide the cotton textile industry into high and low quality market segments and focus on the four main types of raw cotton inputs: Indian cotton, Brazilian cotton, lower-quality U.S. cotton, and higher-quality U.S. cotton.[20] I index these input types, respectively, by $i \in \{I, B, USL, USH\}$. Products in the high-quality market segment are produced using higher-quality U.S. cotton or Brazilian cotton, while low-quality products are produced using lower-quality U.S. cotton or Indian cotton. Thus, within each market segment there are two inputs and the model is identical to that presented in Acemoglu (2002). However, the elasticities of substitution between inputs can vary across the different market segments, and there is also some substitutability in demand between low and high quality products.

3.1 Model setup

The model can be thought of as representing a small textile sector which is embedded in a larger economy, i.e., it is a partial equilibrium model. It is also dynamic, with continuous time. The textile sector produces low-quality and high-quality goods and

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[20] Egyptian cotton, the fourth most important variety, is also a candidate for inclusion here. But that variety was quite similar to Brazilian cotton, and so it is easier to work with only four varieties and think of the Brazilian category as also representing Egyptian cotton.

consumption is over an index Y of these goods which takes a CES form,

$$Y = \left[Y_L^{\frac{\epsilon-1}{\epsilon}} + Y_H^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}},$$

where Y_L is an index over low-quality textiles, Y_H is an index of high-quality textiles, and $\epsilon \in (0, +\infty)$ is the elasticity of substitution between them. The corresponding price index P takes the standard form, where the price indices over low and high-quality goods are, respectively, P_L and P_H. The price index P is the numeraire. The Y_L and Y_H indices are given by,

$$Y_L = \left[y_I^{\frac{\rho_l-1}{\rho_l}} + y_{USL}^{\frac{\rho_l-1}{\rho_l}} \right]^{\frac{\rho_l}{\rho_l-1}} \quad \text{and} \quad Y_H = \left[y_B^{\frac{\rho_h-1}{\rho_h}} + y_{USH}^{\frac{\rho_h-1}{\rho_h}} \right]^{\frac{\rho_h}{\rho_h-1}},$$

where y_i is the quantity of final textile goods produced using inputs of type i. The elasticity of substitution between textiles made with Indian cotton and those made with lower-quality U.S. cotton is $\rho_l \in (0, +\infty)$, while the elasticity of substitution between products made with Brazilian and higher-quality U.S. cotton is $\rho_h \in (0, +\infty)$. The corresponding price indices take the standard CES form.

The production function for each of the final goods is,

$$y_i = \left(\frac{1}{1-\beta} \right) \left(\int_0^{N_i} x_i(k)^{1-\beta} dk \right) Z_i^{\beta}, \tag{1}$$

where N_i is the number of machine types available for producing good i, $x_i(k)$ is the quantity of each machine of type k specialized for the production of good i, Z_i is the input used to produce good i, and $\beta \in (0, 1)$. Inputs correspond to the varieties of raw cotton in the empirical setting, and each input is specific to the good it produces. The price of input i paid by input users, denoted c_i, corresponds to the price of raw cotton variety i on the British market. Note that each machine type is specialized for use with only one input, so the level of technology related to each input type, represented by N_i, is different for each i.[21] The price of machines of type k used with inputs of type i is given by $\chi_i(k)$.

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[21] This includes an implicit assumption that different technologies are used for lower-quality U.S. cotton and higher-quality U.S. cotton.

3.2 Short-run equilibrium (with technology fixed)

For each input type, textiles are produced by perfectly competitive firms which take output prices, input prices, and machine prices as given. It is straightforward to solve the final goods firms' optimization problem in order to obtain expressions for the demand for machines and inputs (details available in Appendix A.2).

Machines are produced by technology monopolists who face a constant marginal cost ψ. The profit for a monopolist producing a machine type k used for good i is $\pi_i(k) = (\chi_i(k) - \psi)x_i(k)$. The demand curve for machines obtained from the final goods producer's optimization problem is isoelastic, so the optimal price charged by these monopolists is $\chi_i(k) = \psi/(1-\beta)$. To simplify things, I normalize $\psi = (1-\beta)$, which implies that equilibrium machine prices are $\chi_i(k) = 1$ for all i and k.[22]

One implication of having perfectly competitive final-goods producing firms and a constant elasticity of substitution between goods in each market segment is that we can obtain expressions for the relationship between relative prices and relative outputs within each segment. For example, within the low-quality textile segment, $p_I/p_{USL} = (y_I/y_{USL})^{-1/\rho_l}$. Using this, Equation 1, and the first-order conditions from the final goods producers' problem, I obtain the following expression for the relationship between relative input prices, relative technology, and relative input quantities within the low-quality textile segment:

$$\frac{c_I}{c_{USL}} = \left(\frac{N_I}{N_{USL}}\right)^{\frac{\sigma_l-1}{\sigma_l}} \left(\frac{Z_I}{Z_{USL}}\right)^{-\frac{1}{\sigma_l}}. \tag{2}$$

In this equation, $\sigma_l = 1-\beta+\beta\rho_l$ is the derived elasticity of substitution between inputs in the low-quality textile market segment. A similar expression can be obtained for the high-quality market segment, where the elasticity of substitution between high-quality inputs is $\sigma_h = 1-\beta+\beta\rho_h$. This useful equation describes the short-run relationship between relative input supplies and relative input prices.

---

[22] Note that, because machine producers are small, the pricing and production decisions of individual producers will not affect Z_i, so machine producers will not consider the impact of their collective pricing choices on the quantity of input i.

> **Short-run prediction:** Holding technology fixed, an increase in Z_i/Z_j within a market segment will decrease c_i/c_j within that segment. E.g, within the low-quality market segment,
>
> $$\left.\frac{\partial ln\left(\frac{c_I}{c_{USL}}\right)}{\partial ln\left(\frac{Z_I}{Z_{USL}}\right)}\right|_{N_I,N_{USL}} = -\frac{1}{\sigma_l} < 0\,.$$

3.3 Incentives and costs of innovation

Next, I consider the long-run setting in which technology is endogenous. Given that machine prices equal one, and using the machine demands from the final-goods producer's first-order condition, instantaneous profits for a technology monopolist firm making machines for industry i are, $\pi_i = \beta\ p_i^{1/\beta}\ Z_i$. Machines depreciate fully after use, but machine designs remain available indefinitely. Thus, technology monopolists care about their discounted value of future profits, rather than instantaneous profits, when deciding whether to develop new machines. The net present discounted value can be written using a standard dynamic programming equation as, $rV_i - \dot{V}_i = \pi_i$, where r is the interest rate, V is the present discounted value of future profits, and π is the flow of profits. Focusing on the steady state, where $\dot{V} = 0$ and the interest rate is constant, the discounted value of developing a machine of type i is,

$$V_i = \frac{\beta p_i^{1/\beta} Z_i}{r}. \tag{3}$$

This expression reveals the two key forces that determine the impact of an increase in Z_i on innovation. An increase in Z_i in Equation 3 has a direct positive influence on the incentives for innovating in technologies that augment input i. Acemoglu calls this the *market size effect*. However, an increase in Z_i will also increase output y_i which will reduce the price p_i. Thus, an increase in Z_i will act to reduce the incentives for innovation in technologies that augment input i through this *price effect*. The relative strength of these two effects will depend on how strongly p_i responds to an increase in Z_i, which depends on the elasticity of substitution between final goods, or equivalently, on the derived elasticity of substitution between inputs.

Using Equation 3, I obtain the relative value of producing each machine type within the low and high quality segments. For example, within the low-quality market segment I obtain,

$$\frac{V_I}{V_{USL}} = \left(\frac{N_I}{N_{USL}}\right)^{-\frac{1}{\sigma_l}} \left(\frac{Z_I}{Z_{USL}}\right)^{\frac{\sigma_l - 1}{\sigma_l}} . \tag{4}$$

This equation shows that, when the elasticity of substitution between factors is high ($\sigma_l > 1$), an increase in the quantity of input i will increase the incentive for new inventions that augment input i. The opposite will occur when $\sigma_l < 1$. Similar results hold in the high-quality market segment.

I now turn to the cost of innovation which is modeled in a very simple way. The production of a new machine design costs a fixed amount η of final output according to the function $\dot{N}_i = \eta R_i$ where R_i represents expenditure, denominated in the index over final goods, on innovation in these machines. For simplicity, I assume that η does not vary across different machine types.[23]

3.4 Long-run results (with technology varying)

I focus on the balanced growth path in which each technology type progresses at the same rate. Within each market segment, balanced growth implies that $\dot{N}_i = \dot{N}_j$ for all i and j. It follows that $\dot{V}_i = 0$ and $V_i = V_j$. Using this together with Equation 4, I can show that in the low-quality market segment it must be the case that,

$$\frac{N_I}{N_{USL}} = \left(\frac{Z_I}{Z_{USL}}\right)^{\sigma_l - 1} . \tag{5}$$

Using this and Equation 2, I derive the long-run relationship between relative quantities and relative prices,

$$\frac{c_I}{c_{USL}} = \left(\frac{Z_I}{Z_{USL}}\right)^{\sigma_l - 2} . \tag{6}$$

Focusing on the low-quality market segment, these equations deliver the following long-run predictions.

---

[23] This assumption could be weakened. Allowing the cost of innovation to differ across different inputs, as in Acemoglu (2002), does not change the main predictions of the theory. However, it is important that these costs do not vary over time.

Long-run predictions: Within the low-quality market segment, an increase in Z_I/Z_{USL} will cause,

1) Directed technical change towards Indian cotton if and only if $\sigma_l > 1$, since,

$$\frac{\partial ln\left(\frac{N_I}{N_{USL}}\right)}{\partial ln\left(\frac{Z_I}{Z_{USL}}\right)} = \sigma_l - 1 \ .$$

2) An increase in the relative price of Indian cotton (strong induced bias) if and only if $\sigma_l > 2$, since,

$$\frac{\partial ln\left(\frac{c_I}{c_{USL}}\right)}{\partial ln\left(\frac{Z_I}{Z_{USL}}\right)} = \sigma_l - 2 \ .$$

Analogous results will hold in the high-quality market segment depending on the value of σ_h.

These two results are familiar from Acemoglu (2002). Thus, within a market segment the theory reproduces the key results of Acemoglu's theory. While the result above will be my primary focus in the empirical exercise, the model also makes predictions across market segments. Equation 7 describes the relationship between technology and input quantities for inputs in two different market segments (in this case Indian and Brazilian cotton) on the BGP:

$$\frac{Z_I}{Z_B} = \left(\frac{N_I}{N_B}\right)^{\frac{1}{\kappa-1}} \frac{\left[1 + N_{USL}/N_I\right]^{\frac{\sigma_l-\kappa}{(1-\sigma_l)(1-\kappa)}}}{\left[1 + N_{USH}/N_B\right]^{\frac{\sigma_h-\kappa)}{(1-\sigma_h)(1-\kappa)}}} \ , \tag{7}$$

where $\kappa = 1 - \beta - \beta\epsilon \in (0, +\infty)$ is the derived elasticity of substitution between inputs from two different market segments holding constant the relative quantities of inputs within each market segment.[24] This equation tells us that when $\kappa > 1$, holding relative input quantities (and thus relative technologies) constant in each market segment, an increase in Z_I/Z_B will increase N_I/N_B. Thus, the predictions regarding directed technical change across market segments are similar to those within a market segment.

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[24] This equation is derived in Appendix A.2.

3.5 Dynamics

In the empirical setting, we will think of the Civil War as a shift in the balanced growth path which, *ex post*, we know was only temporary but which agents believed was at least potentially permanent *ex ante*.[25] Thus, we will primarily observe the response along the transition toward a new balanced growth path, and then, after the war, the slow transition back to a balanced growth path, similar to the original, as U.S. cotton production recovered. A brief discussion of the model dynamics is therefor needed.

Consider an economy that begins on the balanced growth path and then experiences a shock to relative input quantities. In particular, suppose that there is an increase in Z_I/Z_{USL}, Z_B/Z_{USH}, and Z_I/Z_B, as observed in the empirical setting.

Free entry of innovative firms implies that the cost of innovation must be greater than or equal to the value of a new invention, i.e., $\eta \geq \max[V_I, V_B, V_{USL}, V_{USH}]$ with $\eta > V_i$ implying $\dot{N}_i = 0$. Within the low-quality market segment, if $\sigma_l > 1$, a shock that increases Z_I/Z_{USL} implies $V_I > V_{USL}$. Thus, for some period of time any innovation in that market segment must be confined to technologies related to Indian cotton.[26] A similar result will hold in the high-quality market segment.

For inputs in two different market segments (in this case Indian and Brazilian cotton) the relative value of technologies is,

$$\frac{V_I}{V_B} = \left(\frac{Z_I}{Z_B}\right)^{\frac{\kappa-1}{\kappa}} \left(\frac{N_I}{N_B}\right)^{-\frac{1}{\kappa}} \frac{\left[1+\left(\frac{N_I}{N_{USL}}\frac{Z_I}{Z_{USL}}\right)^{(1-\sigma_l)/\sigma_l}\right]^{\frac{\sigma_l-\kappa}{(1-\sigma_l)\kappa}}}{\left[1+\left(\frac{N_B}{N_{USH}}\frac{Z_B}{Z_{USH}}\right)^{(1-\sigma_h)/\sigma_h}\right]^{\frac{\sigma_h-\kappa}{(1-\sigma_h)\kappa}}}, \qquad (8)$$

Holding the ratios of input supplies within each market segment constant, we can see that an increase in Z_I/Z_B increases V_I/V_B, when $\kappa > 1$. Thus, starting from the balanced growth path, a shock that increases Z_I/Z_B with the input supply ratios constant within market segments implies that, on the transition path back to the BGP, innovation can occur in at most one market segment. Things are slightly more complicated when input supply ratios within market segments also change. However, if the net effect of the changes in input supplies is to increase (starting from the BGP)

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[25] See the last paragraph in Section 2.3.

[26] The formal proof is analogous to that given in Acemoglu & Zilibotti (2001) (p. 601-2).

the right hand side of Equation 8, then on the transition path innovation will initially be confined to technologies used in the low-quality market segment, and within that market segment innovation will be focused on only one technology type.

One result of this discussion is that it reveals why, even when the model predicts that a shock will increase both N_I/N_{USL} and N_B/N_{USH}, on the transition path we may initially observe only innovation in technologies related to Indian cotton. The intuition here is that even though the shortage of U.S. cotton may increase the incentives to innovate in both Indian and Brazilian cotton technologies (relative to U.S. cotton technologies), it may also increase the incentives for innovating in Indian cotton technologies relative to Brazilian cotton technologies (i.e., increasing V_I/V_B). In this case, the model predicts that, initially on the transition path, we will observe only innovation in technologies related to Indian cotton. This provides one (of several) explanations for why, as we will see, innovation during the Civil War period appears to have focused primarily on technologies related to Indian cotton.

4 Data

4.1 Patent data

The primary data used to measure innovation in this study come from British patent records. While imperfect, patent data is the best available quantifiable measure of technological advance during this period.[27] 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 will draw heavily on the detailed information available in the patent descriptions. While British patent laws changed in 1852 and 1883, they were stable during the period of this study.

One disadvantage of using patent data is that it will not capture all types of innovation. Evidence from Moser (2010) shows that a significant fraction of new inventions went unpatented during the period I study. However, her results also suggest that,

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[27] 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).

among all categories, inventions of manufacturing machinery – the primary focus of this study – were the most likely to be patented.[28] 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.[29] 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 will primarily be on two BPO categories, "Preparation & Spinning" and "Weaving & Finishing".[30] The Preparatory & Spinning category includes technologies related to the preparation of raw cotton, such as cotton gins and carding machines, machines used in the spinning process, such as mules, yarn types, and other related technologies. The Weaving & Finishing category includes technologies such as looms, fabrics, and fabric treatments.

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.* (2008)).[31] This database provides the titles of the patents, which are not available in the patent data I collected. Using these titles, I identify patents related to the main textile inputs:

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[28] Moser (2010) 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.

[29] These data include both granted patents and those which received provisional protection but where a patent was not ultimately granted.

[30] 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.

[31] 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.

cotton, wool, linen/flax, and silk.[32] Consistent patent titles are available from 1853-1870.[33]

Conveniently, 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. Further information on the British patent system is available in Appendix A.3.

Within each BPO technology category, patents may also be listed in various technology subcategories. For example, within the BPO Preparatory & Spinning technology category, it is possible to identify patents falling into subcategories such as "Gins", "Mules and Twiners", "Carding Machines", etc. Data were gathered on patents fitting into several of the larger technology subcategories, which are listed in Table 1.[34] These subcategory data are available from 1855-1876.

Table 1: Preparatory & Spinning technology subcategories by production stage

Preparatory stage	**Patents**	**Spinning stage**	**Patents**	**Finishing stage**	**Patents**
Gins	122	Mules and twiners	446	Finishing	332
Openers/scutchers	331	Rollers for spinning	462		
Carding	696	Bearings for spinning	242		
Combing	354				

Patent counts for BPO Preparatory & Spinning technology subcategories, 1855-1876.

4.2 Patent quality measures

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. I take advantage of three measures of patent quality in order to evaluate

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[32] Details of the patent title search are available in Appendix A.3. This technique has been used previously with these data by Brunt *et al.* (2008).

[33] After 1870 there was a clear structural change in the naming conventions, with less detail included in the patent titles. The average number of characters in the patent titles is over 70 for the years before 1871. This drops to just under 28 characters on average starting in 1871.

[34] Note that "finishing stages of the spinning process" denotes operations occurring as part of the spinning stage of production, such as bleaching or dyeing yarn, as opposed to the finishing stage of the textile production process as a whole, which involved bleaching, dyeing, etc. of woven fabrics. Thus, it falls into the Preparatory & Spinning category rather than the Weaving & Finishing category.

whether the 1861-1865 period was also characterized by an increase in the number of high-quality cotton-textile-related patents. The first measure is based on the payment of patent renewal fees. These were expensive fees that 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.[35] 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.[36] The second quality measure is based on mentions of the patent in a contemporary periodical, *Newton's London Journal*.[37] 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. The third quality measure is the based on whether technologies patented in Britain were also filed in India.[38] Patents of innovations which proved to be particularly useful are presumably more likely to be patented in multiple locations. While similar, each of these three measures captures a distinct aspect of patent quality. Most of these quality measures are based on new data sets collected for this purpose. A detailed description of these data are available in Appendix A.3.

4.3 Price and quantity data

To evaluate the strong induced-bias hypothesis, new price data was gathered from market reports printed in *The Economist* magazine. The data cover 1852-1880. While the data were collected on a monthly basis, I aggregate to quarters to reduce short-term volatility and measurement error. These data are available for the following benchmark cotton varieties: Upland Middling from the U.S., 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

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[35] 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.* (2008)).

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

[37] A similar approach has previously been used to value historical British patents by Nuvolari & Tartari (2011).

[38] This approach has been used previously by Lanjouw *et al.* (1998).

Ordinary was a lower-quality variety that was more comparable to Indian cotton. Thus, in relating the data to the theory, Upland Ordinary will represent lower-quality U.S. cotton and Upland Middling will represent higher-quality U.S. cotton.[39] When longer series are needed I will supplement these data with less detailed annual data from Mann (1860) covering 1820-1859 and Ellison (1886) covering 1820-1884. I also need data on the quantity of cotton imported by Britain from each of the major suppliers. For this purpose, I use annual data from either Ellison (1886) for 1820-1884 or Mann (1860) for 1820-1859.

4.4 Weather data

In order to estimate the elasticity of substitution between inputs, I will use data on the average length of the growing season between first bloom and first frost in the U.S. as an instrument for the supply of U.S. cotton. The main data were collected from the New York Times (Oct. 8, 1866) and cover 1837-1860. 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.[40]

5 Directed technical change

This section explores the impact of the Civil War shock on innovation patterns. I proceed in two steps. First, I look at patent data on the broad technology categories related to textile production in order to establish that there was a significant increase in textile-related innovation in response to the shock. Further, I show that this increase was concentrated in technologies related to cotton textiles and that no similar increase occurred for technologies related to wool, linen, or silk textiles. These results

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[39] One indicator that comparing the lower-quality Upland Ordinary cotton to Indian cotton makes sense is that Indian cotton is more strongly correlated with the Upland Ordinary (0.9946) than with the Upland Middling price (0.9937). In contrast the higher-quality Brazilian and Egyptian cotton varieties show a stronger correlation with the Upland Middling (0.9941 and 0.9858 respectively) than with the Upland Ordinary price (0.9923 and 0.981 respectively). The two U.S. cotton varieties, which are subject to many common shocks, have the highest correlation (0.9982).

[40] 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." Of the two pieces of information available, it appears that the date of the first frost is somewhat more important, since the frost ends the chances of any further growth.

show that the shock generated a significant response by textile innovators, and that this response was concentrated in cotton textile technologies. However, since these patterns do not reveal shifts in the direction of technological progress across cotton types, my discussion of these patterns will be brief.

Second, I use data on patents related to specific types of textile machinery in order to assess the influence of the shock on the *direction* of technological progress. Three types of textile machinery – gins, openers/scutcher, and carding machines – were particularly important for using Indian cotton. A shift in innovation towards these machine types can thought of as an increase in N_I relative to other technology types. Thus, these results reveal the impact of the change in relative input supplies (Z_I/Z_{USL}) on relative technology levels (N_I/N_{USL}).

5.1 Overall impact of the shock on textile technologies

I begin by looking at patenting patterns in the 146 broad technology categories identified by the British Patent Office. Two of these, “Preparatory & Spinning” and “Weaving & Finishing”, include the main textile technologies. The first of these includes all technologies used in the early stage of the production process while the second contains technologies used in the later stages of the production process. These broad categories include, in addition to technologies related to cotton textiles, those related to wool, linen, silk, and other textile industries.

Our first glimpse of the patent data is presented in Figure 5. The left-hand panel graphs patent counts for the two main textile technology categories. The right-hand panel shows similar data for all other BPO technology categories. Even in the broad Preparatory & Spinning technology category it is clear that the shock generated a response by innovators in these technologies. These graphs suggest that there was an increase in patents in the Preparatory & Spinning technologies during the 1861-1865 period, but no similar increase in the textile technologies used in the later stages of production, nor in non-textile technologies.[41]

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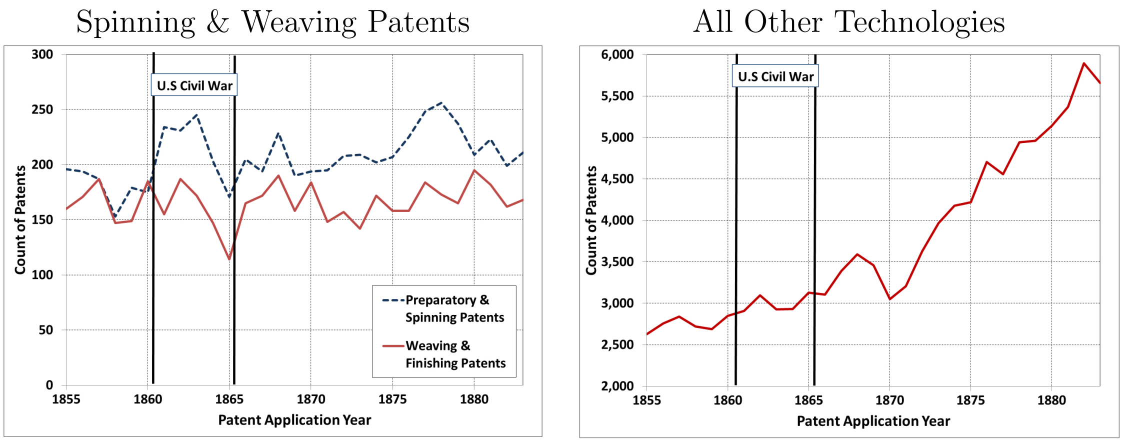
[41] These patterns are explored econometrically in Appendix A.4.

Figure 5: Patent counts for BPO technology categories, 1855-1883


Spinning & Weaving Patents

All Other Technologies

Annual data from 1855-1883.

Next, I look at whether there was an increase in patents related to cotton textiles compared to patents for technologies used with the other textile inputs. Figure 6 graphs these data. We can see that there was a substantial increase in cotton textile technology patents at the onset of the war. More importantly, there was a sustained high level of cotton textile technology patents throughout the Civil War period, with the level dropping only in early 1865 as the war wound down.

These patterns are established econometrically in Appendix A.4.1. First, using a panel data regression approach I show that there was a statistically significant increase in the level of cotton textile patents during the shock period, relative to wool, linen, and silk-related patents. Then, using wool, linen, and silk to control for time-varying factors, I focus on the timing of the impact on the cotton textile industry. I find that the increase in cotton textile patents started in 1861 and persisted through 1865, with the peak level occurring in 1864 in most specifications. The fact that the peak occurs several years into the war is particularly important, since, consistent with the evidence on the lag in innovation discussed in Section 2.5, these are likely to represent new innovations.[42] Thus, it appears that the Civil War led to a significant increase in innovation in cotton textile technologies.

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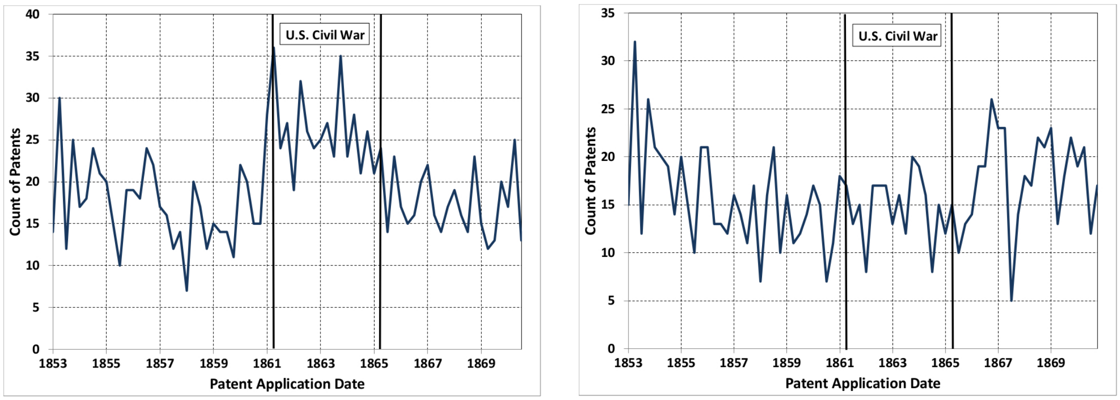
[42] In contrast, the initial spike in patents was almost certainly due to the patenting of existing (but not yet widely implemented) ideas which suddenly became valuable as a result of the onset of the war.

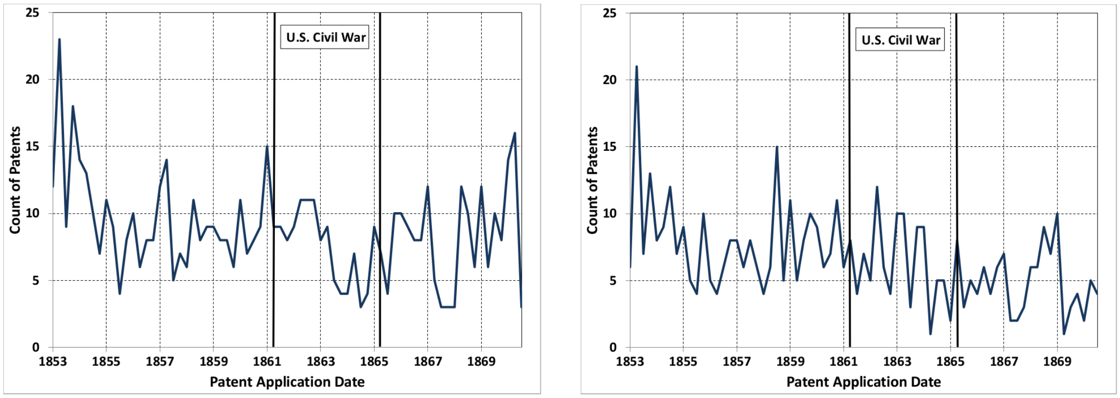
Figure 6: Count of patents with titles mentioning main textile inputs, 1853-1870

Cotton-related patents Wool, linen and silk-related patents

Cotton patents Wool patents



Linen patents Silk patents



Quarterly data from 1853-1870.

5.2 Impact on the direction of technological progress

To investigate the direction of the technical change that occurred during the Civil War, I use the data on patents in technology subcategories within the BPO Preparatory & Spinning technology category, shown in Table 1. Two of these subcategories, gins, and openers/scutchers (and to a lesser extent, carding machines) can be directly linked to the use of Indian cotton because they address the main technological bottlenecks in the use of that variety.

I begin the analysis by graphing the count of patents, by year, for each technology subcategory, in Figure 7. These graphs show an increase in patents in technology subcategories related to the preparation of raw cotton, particularly gins and openers/scutchers, during the 1861-1865 period. In contrast, other preparatory and spinning technologies do not show similar responses. It is particularly interesting that we observe no strong response in combing technologies, which generated the largest amount of cotton waste, and a weak response in carding technologies, the second largest waste generator. If innovation had been focused primarily on economizing on waste cotton, I would expect to see an increase in these technology categories. The fact that we do not suggests that innovation was not directed towards economizing on cotton in general.[43]

Next, I analyze these patterns using a regression approach. First, I want to test whether the gins and openers/scutchers subcategories are exhibiting different behavior during the shock period relative to the other technology subcategories within the set of textile technologies, without imposing the assumption that only those categories might respond to the shock. A good starting point is to pool data from all eight technology subcategories, indexed by $j \in J$, and run a fixed effect regression such as,

$$P_{jt} = \alpha + \left(\sum_{j=1 \in J} \gamma_i \times S_t \times \phi_j \right) + \Psi_j + \xi_t + TT_{jt} + e_{jt}, \tag{9}$$

where P_{jt} is the count of patents in subcategory j, S_t is an indicator variable for the shock period, ϕ_j is an indicator variable for subcategory j, Ψ_j is a full set of subcategory-specific indicator variables, TT_{jt} is a subcategory-specific time-trend, ξ_t is a set of year indicator variables for all years outside of the shock period, and e_{jt} is an error term.[44] For now, the shock period is 1862-1865. I omit 1861 from the shock period because it seems unlikely that an increase in patents during 1861 could

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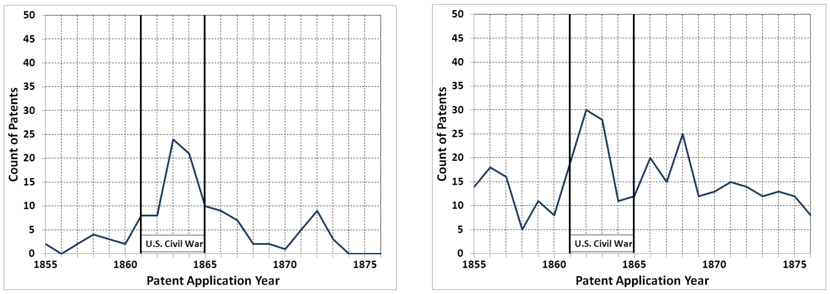
[43] Combing machines were not used in producing every type of yarn, but when they were used they were the largest source of cotton waste (Thornley (1912)). Combing machines act somewhat like a standard comb. Their purpose was to remove short fibers and arrange the remaining longer fibers so that they are all pointing the same direction. Combing was generally done when producing higher quality fabrics. While combing machines were used to produce cotton, they were more common in the preparation of wool (worsted) textiles. Part of the reason we may not observe a response in combing technologies is that producers might have moved away from the use of using combing machines. The second largest waste generator was carding, a technology that was used in essentially all production processes and which could not have been avoided by producers.

[44] I must omit indicator variables for years within the shock period since these will be perfectly correlated with the full set of subcategory x year indicator variables for each of the shock period years.

Figure 7: Patent counts in subcategories of the BPO Spinning technology category

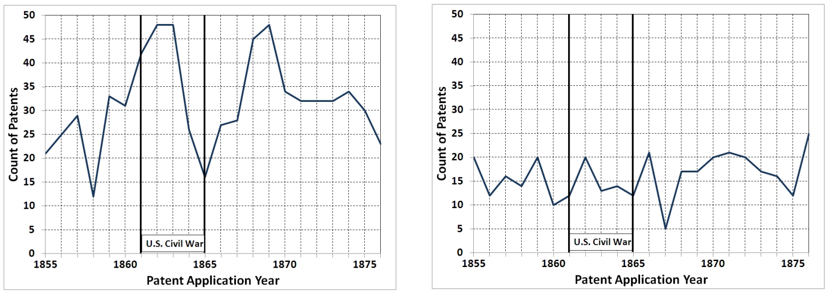
Gins

Openers, scutchers, etc.



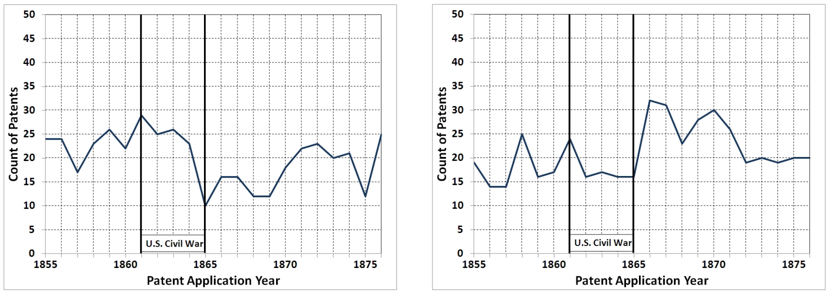
Carding machines

Combing machines



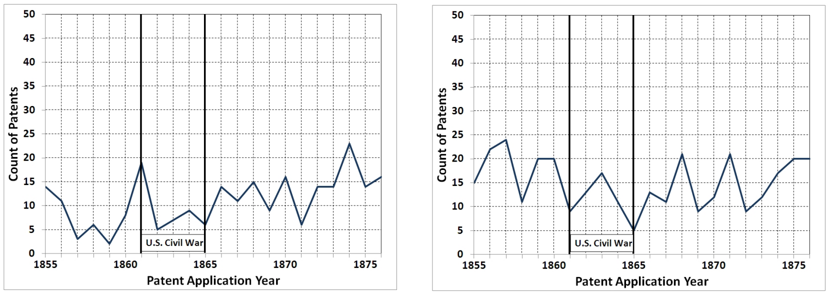
Mules

Rollers, etc.



Bearings, etc.

Finishing



represent truly new ideas (later I will investigate the timing of these effects in more detail). The fixed-effect regression results are presented in columns 1-2 of Table 2. These results show that there was a significant increase in gin patents during the 1862-1865 period. Openers and scutchers display an positive and statistically significant coefficient in these specifications. None of the other technology types experienced a statistically significant increase in patenting during the 1862-1865 period.

There are several potential concerns with these results. One concern is serial correlation, which Bertrand *et al.* (2004) have shown can be a serious concern in a panel data setting. Durbin-Watson statistics suggest that serial correlation is not a major concern in the panels I study (see Appendix A.4). However, we may still be worried. A second concern is that there may be correlated errors across different technology subcategories. One approach to addressing these concerns is by using a Feasible Generalized Least Squares (FGLS) that allows for autocorrelation as well as correlated errors across panels. Columns 3-4 of Table 2 present results estimated using this approach. This alternative approach suggests that both gins and openers/scutchers experienced statistically significant increases during the 1862-1865 period.

Another potential concern is that there are a small number of zeros in the data, so we may need to apply count data methods.[45] In order to deal with any potential bias that these may create, I calculate additional results using Negative Binomial regressions.[46] These are shown in columns 5-6 of Table 2. Again, this modification does not affect the basic results, though the increase in openers/scutchers patents is no longer statistically significant.

An even stronger approach to addressing both serial correlation and zeros in the data is to aggregate the data into pre-shock, shock, and post-shock periods, as suggested by Bertrand *et al.* (2004). This eliminates the time dimension of the data and all zero observations, but also reduces the size of the available data set, which may affect the significance of the results. Results generated using this aggregated approach are shown in Table 3. Since there are no zeros in these data and I cannot include time trends, I also include regressions in which the dependent variable is the log of patents. Columns 1-2 present results in which the shock period is 1861-1865. In column 3-4, 1861 is dropped from the data entirely and the focus is on the 1862-

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[45] Four out of 176 subcategory-year bins include zero patents.

[46] Negative Binomial regressions are preferred to Poisson regressions because most of the data series are characterized by overdispersion. Poisson regression results are available in Appendix A.4.

Table 2: Panel regressions across textile technology subcategories

	Dependent Variable: Number of patents					
	FE regressions		**FGLS regressions**		**NegBin regressions**	
	(1)	(2)	(3)	(4)	(5)	(6)
Bearings x Shock period	-6.562*	-4.532	-5.479**	-2.716	-0.628**	-0.481*
	(3.617)	(4.367)	(2.743)	(2.399)	(0.255)	(0.275)
Carding x Shock period	2.132	3.938	2.293	3.703	-0.0232	0.0527
	(3.617)	(4.367)	(5.645)	(5.520)	(0.166)	(0.209)
Combing x Shock period	-3.007**	-1.494	-1.088	0.241	-0.178	-0.0997
	(3.617)	(4.367)	(2.025)	(2.258)	(0.198)	(0.232)
Finishing x Shock period	-5.757***	-4.964	-3.729	-3.294	-0.415*	-0.383
	(3.617)	(4.367)	(3.231)	(3.102)	(0.219)	(0.255)
Gins x Shock period	11.10***	12.14***	14.29***	15.28***	1.463***	1.474***
	(3.617)	(4.367)	(1.967)	(2.238)	(0.209)	(0.249)
Mules x Shock period	-0.479	-0.0698	0.368	1.583	-0.0528	-0.0278
	(3.617)	(4.367)	(3.127)	(3.199)	(0.182)	(0.225)
Openers x Shock period	4.993***	5.883*	6.543**	7.472**	0.257	0.299
	(3.617)	(4.367)	(3.025)	(3.018)	(0.180)	(0.224)
Rollers x Shock period	-7.174***	-5.490	-5.840**	-4.063	-0.363*	-0.284
	(3.617)	(4.367)	(2.949)	(3.107)	(0.197)	(0.228)
Subcategory TT (p value)		[0.318]		[0.007]		[0.071]
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176	176	176	176	176	176
Number of subcategories	8	8	8	8	8	8

Regressions run on annual panel data from 1855-1876. The shock period is 1862-1865. All regressions include subcategory-specific fixed effects. Standard errors are shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. In the FE specification, heteroskedasticity-robust standard errors are not used because conventional standard errors turn out to be more conservative. In the FGLS specifications, standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. Year effects for the shock period years are not included.

1865 period. In columns 5-6, both 1861 and 1862 are dropped from the data to focus only on innovation during the last three years of the war. In all cases I observe a statistically significant increase in gin patents during the Civil War. There is limited evidence of an increase in openers/scutchers patents. However, no other categories show consistent evidence of unusual patenting patterns during the shock period.

Table 3: Panel regressions aggregated across pre-shock, shock, and post-shock periods

	All data		**Dropping 1861**		**Dropping 1861-1862**	
Dependent Variable:	Pats /Year	Log Pats/Year	Pats Year	Log Pats/Year	Pats Year	Log Pats/Year
Shock period:	1861-1865		1862-1865		1863-1865	
	(1)	(2)	(3)	(4)	(5)	(6)
Bearings x	-0.206	0.00772	-2.656	-0.302	-2.073	-0.219
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Carding x	7.995*	0.317	6.495	0.275	1.995	0.135
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Combing x	-0.979	-0.0412	-0.429	-0.00324	-2.179	-0.130
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Finishing x	-4.664	-0.322	-4.164	-0.277	-4.664	-0.322
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Gins x	12.56**	1.745***	14.11**	1.848***	16.69***	2.000***
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Mules x	3.482	0.213	1.882	0.139	0.548	0.0735
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Openers x	7.942	0.515*	8.192*	0.528*	4.942	0.353
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Rollers x	-1.962	-0.0507	-3.512	-0.142	-3.429	-0.137
Shock period	(4.193)	(0.270)	(4.193)	(0.270)	(4.193)	(0.270)
Post-shock	2.339	0.195	2.339	0.195	2.339	0.195
indicator	(1.677)	(0.108)	(1.186)	(0.0763)	(1.677)	(0.108)
Observations	24	24	24	24	24	24
Number of subcat_code	8	8	8	8	8	8

Data from 1855-1876 that has been aggregated to three periods: pre-shock (1855-1860), shock, and post-shock (1866-1876). The left-hand side variable is the average number of patents in each category in each period or the log of the average number of patents. All regressions include an indicator variable for the post-shock period. Standard errors are not heteroskedasticity robust because conventional standard errors turn out to be more conservative in this setting. *** p<0.01, ** p<0.05, * p<0.1.

Next, I explore the timing of these impacts, focusing on the gins and openers/scutchers technologies. To do so, I look for changes in patenting patterns in these technologies starting up to three years before the Civil War and extending up to three years after, relative to the remaining six technology subcategories. The basic specification is,

$$P_{jt} = \alpha + \left[\sum_{k=1858}^{1868} (\gamma_k^G \times YR_k \times GINS_j) \; + \; (\gamma_k^O \times YR_k \times OPENERS_j) \right] + \Psi_j + \xi_t + TT_{jt} + \epsilon_{jt}$$

where $GINS_j$ and $OPENERS_j$ are indicator variables for the gins and openers/scutchers subcategories, respectively, and YR_k is an indicator variable for year k.

The results are shown in Table 4 which presents fixed effect regression results in columns 1-2, results generated using FGLS in columns 3-4, and additional Negative Binomial regression results in columns 5-6. These results consistently show that patents of gins increased at the start of the Civil War in 1861, reached the highest level 2-3 years into the war (1863-1864), and then tapered off towards the end of the war. The openers/scutchers category shows consistent evidence of an unusually high level of patents in 1862-1863.

The results shown in Tables 2-4 suggest that the Civil War period was characterized by an increase in innovation in those technologies related to Indian cotton. This is the main result of the paper related to directed technical change. The remainder of this section investigates the robustness of these observed effects.

Table 4: Timing of effects on gins and openers/scutchers technologies

	FE regressions		**FGLS regressions**		**NegBin regressions**	
	(1)	(2)	(3)	(4)	(5)	(6)
Gins x 1858	6.409	5.500	5.911***	4.478**	0.894	0.974
	(6.524)	(6.851)	(2.155)	(2.182)	(0.565)	(0.642)
Gins x 1859	1.076	0.258	-0.0358	-1.918	0.371	0.435
	(6.524)	(6.769)	(2.216)	(2.250)	(0.633)	(0.689)
Gins x 1860	1.576	0.848	2.392	0.982	0.0358	0.0939
	(6.524)	(6.695)	(2.223)	(2.235)	(0.755)	(0.792)
Gins x 1861	3.076	2.439	3.918*	2.636	1.201***	1.247***
	(6.524)	(6.628)	(2.224)	(2.211)	(0.431)	(0.483)
Gins x 1862	4.409	3.864	4.427**	2.889	1.285***	1.315***
	(6.524)	(6.570)	(2.225)	(2.190)	(0.433)	(0.470)
Gins x 1863	20.24***	19.79***	20.70***	19.59***	2.369***	2.395***
	(6.524)	(6.521)	(2.224)	(2.171)	(0.317)	(0.354)
Gins x 1864	22.08***	21.71***	23.27***	22.44***	2.455***	2.486***
	(6.524)	(6.480)	(2.223)	(2.156)	(0.330)	(0.353)
Gins x 1865	16.74**	16.47**	17.14***	16.36***	2.132***	2.149***
	(6.524)	(6.448)	(2.221)	(2.144)	(0.414)	(0.420)
Gins x 1866	6.076	5.894	5.685**	4.936**	1.391***	1.397***
	(6.524)	(6.425)	(2.214)	(2.133)	(0.415)	(0.416)
Gins x 1867	7.576	7.485	7.802***	7.569***	1.356***	1.343***
	(6.524)	(6.411)	(2.194)	(2.123)	(0.456)	(0.452)
Gins x 1868	-2.591	-2.591	-1.426	-1.784	-0.165	-0.186
	(6.524)	(6.407)	(2.111)	(1.966)	(0.753)	(0.747)
Openers x 1858	-3.773	-7.362	-6.205***	-6.837***	-0.672	-0.885*
	(6.524)	(6.851)	(2.043)	(1.543)	(0.520)	(0.517)
Openers x 1859	-2.106	-5.336	-3.660	-6.471***	-0.137	-0.332
	(6.524)	(6.769)	(2.323)	(1.496)	(0.371)	(0.372)
Openers x 1860	-3.606	-6.478	-5.261**	-6.911***	-0.384	-0.555
	(6.524)	(6.695)	(2.416)	(1.513)	(0.424)	(0.419)
Openers x 1861	2.894	0.381	3.150	1.209	0.258	0.102
	(6.524)	(6.628)	(2.453)	(1.494)	(0.297)	(0.296)
Openers x 1862	15.23**	13.07**	16.57***	13.62***	0.796***	0.655***
	(6.524)	(6.570)	(2.467)	(1.486)	(0.255)	(0.253)
Openers x 1863	13.06**	11.27*	13.23***	11.44***	0.715***	0.597**
	(6.524)	(6.521)	(2.471)	(1.475)	(0.261)	(0.256)
Openers x 1864	0.894	-0.542	1.799	1.022	0.00822	-0.0785
	(6.524)	(6.480)	(2.466)	(1.468)	(0.373)	(0.362)
Openers x 1865	7.561	6.484	8.608***	6.740***	0.512	0.442
	(6.524)	(6.448)	(2.448)	(1.461)	(0.371)	(0.357)
Openers x 1866	5.894	5.176	6.916***	4.877***	0.382	0.331
	(6.524)	(6.425)	(2.404)	(1.456)	(0.293)	(0.281)
Openers x 1867	4.394	4.035	3.670	2.899**	0.312	0.271
	(6.524)	(6.411)	(2.293)	(1.439)	(0.331)	(0.318)
Openers x 1868	9.227	9.227	9.364***	8.817***	0.543**	0.528**
	(6.524)	(6.407)	(1.982)	(1.326)	(0.269)	(0.258)
Subcategory TT (p value)		[0.177]		[0.000]		[0.006]
Subcategory FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176	176	176	176	176	176
Number of subcategories	8	8	8	8	8	8

Regressions run on annual panel data from 1855-1876. Standard errors are shown in parenthesis. In the fixed effect specification, conventional standard errors are shown as these turn out to be more conservative than robust standard errors. In the FGLS specifications, standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include subcategory fixed effects and year effects. The indicator variable for the first year is omitted.

Using information on both the textile industry and the technology subcategory to which a patent belongs, it is possible to verify that the increase in gins and openers/scutcher innovations was concentrated in the cotton textile industry. When cutting the data at such a fine level, I end up with a number of industry x subcategory x year bins with zero patents, so this analysis relies entirely on Negative Binomial regressions.[47] This fine cut of the data will also make it less likely that we observe statistically significant results. The specification is,

$$P_{ijt} = f\left[\left(\sum_{i=1}^{I}\sum_{j=1\in J}\gamma_{ij}\times S_t\times I_i\times\phi_j\right)+\Psi_j+\theta_i+\xi_t+e_{ijt}\right],$$

where i indexes industries (cotton, wool, linen, and silk), j indexes technology subcategories, S_t is an indicator variable for the shock period (1861-1865), I_i is an indicator variable for industry i, and ϕ_j is an indicator variable for technology j. The model includes a full set of industry fixed effects θ_i, subcategory fixed effects Ψ_j, and year effects ξ_t for all years outside of the shock period.[48]

Table 5 presents the results, which are generated from a single regression but are displayed by industry and subcategory. It is clear from this graph that the increase in gin patents was concentrated in the cotton textile industry and in fact gin technologies were simply not used in the Linen and Silk industries. For openers/scutchers, I observe negative coefficients for all of the industries other than cotton. Note that the results for openers were weaker than those for gins, so it is not surprising that with this very fine cut of the data the cotton x openers coefficient is not statistically significant, though it remains positive.[49]

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[47] Poisson regression are available in Appendix A.4. In general the Negative Binomial results are more conservative (less likely to be statistically significant) than the Poisson regression results.

[48] Note that some patents mention that the technology may be used in multiple industries. In these cases, the patent will be counted towards each industry in which the technology can be applied. Since most of this spillover is from technologies developed for the cotton textile industry which could also be used in other industries, this will tend to bias the results against finding a significant response of cotton textile technologies to the shock.

[49] The increase in the cotton openers/scutchers category is statistically significant if a Poisson regression approach is used.

Table 5: Subcategory x industry x shock period coefficient estimates

	Bearings	Carding	Combing	Finishing	Gins	Mules	Openers	Rollers
Cotton	-0.564	0.00453	-1.668***	-0.512	1.686***	0.254	0.360	-0.475
	(0.414)	(0.304)	(0.422)	(0.446)	(0.326)	(0.334)	(0.314)	(0.338)
Wool	-0.731	-0.341	0.157	-0.479	-1.242	-0.628	-0.588	-0.693*
	(0.500)	(0.339)	(0.320)	(0.506)	(0.770)	(0.455)	(0.404)	(0.388)
Linen	-0.829	-0.807	-0.334	-0.171	NA	-1.014	-0.973	-0.134
	(0.766)	(0.497)	(0.439)	(0.653)		(0.766)	(0.646)	(0.439)
Silk	-1.515	NA	-0.0388	1.222***	NA	-1.700	-0.119	-1.225*
	(1.043)		(0.407)	(0.420)		(1.042)	(0.477)	(0.645)

Coefficient estimates are all from a single Negative Binomial regression run on panel data with two cross-sectional dimensions (industries and subcategories). Annual data from 1855-1876. The shock period is 1862-1865. Regression includes a full set of industry fixed effects, subcategory fixed effects, and year indicator variables. Negative Binomial regressions are warranted because the data are sparse, with 263 out of 704 subcategory x industry x year bins having zero patents.

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 gins and openers/scutchers patents during the Civil War period, I use,

$$P^H_{jt} = \alpha + \beta^G(GINS_j \times S_t) + \beta^O(OPENERS_j \times S_t) + \Psi_j + \xi_t + \epsilon_{jt}.$$

where P^H_{jt} is the count of high-quality patents of technology type j.

I approach this estimation in two ways. First, I run Poisson regressions on the full set of panel data. Poisson regressions are used because the data include a number of zeros but Negative Binomial regressions often fail to converge. Second, I aggregate the data into pre-shock, shock, and post-shock periods and use fixed-effects regressions. This approach sharply limits the set of available data, but it also avoids concerns of serial correlation and worries about zeros in the data. We should keep in mind that all of these results rely on fewer years and more sparse data than the main results.

The first two columns of Table 6 presents the results using the patent renewal data. The estimated coefficients show the increase in the number of gins and openers/scutchers patents filed during the Civil War period which were subsequently renewed at year three. There is also evidence of an increase in patents filed during this period for which the second renewal fee was paid to at year seven, but those data are too sparse to permit statistical analysis.[50] The second two columns of Table 6 conduct a similar exercise using data on whether a patent was mentioned in Newton's London Journal. In general, these results show evidence of an increase in high-quality gin patents during the Civil War period, though the coefficient in column 4 is not statistically significant due to the very small number of observations being used. All specifications show a positive coefficient for openers/scutchers as well, but it is never statistically significant. In addition, Appendix A.5.1 presents evidence that there was an increase in patents of cotton textile related technologies, and gins in particular, in India during the Civil War.

Table 6: High-quality gins and openers/scutchers patents during the U.S. Civil War

	Patents with renewal fees paid at year three		Patents with abstracts in *Newton's London Journal*	
	Full panel	Aggregated	Full panel	Aggregated
Gins x	2.017***	4.817**	2.197***	1.738
Shock period	(0.463)	(1.746)	(0.612)	(0.999)
Openers x	0.235	1.467	0.716	0.214
Shock period	(0.301)	(1.746)	(0.539)	(0.999)
Subcategory FEs	Yes	Yes	Yes	Yes
Time period effects	Yes	Yes	Yes	Yes
Observations	112	24	80	16
Number of panels	8	8	8	8

Column 1 contains results from a Poisson regression run on annual data from 1856-1869. The shock period is 1862-1865. In column 2, these data have been averaged in each of the pre-shock (1856-1860), shock (1862-1865), and post-shock (1866-1869) periods and a fixed effect regression is used. Columns 3-4 use data from 1854-1864. Column 3 contains results from a Poisson regression (Negative Binomial regressions failed to converge). The shock period is 1862-1864. In column 4, these data have been averaged in each of the pre-shock (1854-1860) and shock (1862-1864) periods and a fixed effect regression is used.

These results give us some confidence that the increase in patents during the 1862-1865 period represents new inventions, rather than patents of existing ideas. Had the high-value technologies represented by these results been available prior to 1861, they likely would have been worth patenting, particularly given that the initial patenting fee was only one-half of the renewal fees. Thus, these technologies were most likely not available prior to 1861.

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[50] Graphs of these data and further details are available in Appendix A.4.

Together, the results presented in this section suggest that there was an substantial increase in cotton textile patents during the Civil War period and that this increase was driven by patents of cotton gins, a technology which was particularly important for the use of Indian cotton. Patenting of gins reached its peak two to four years into the war. Moreover, patents of high-quality gin technologies also increased during the war. There is also some evidence of an increase in openers/scutchers patents, but this result is not always robust. These results indicate that the Civil War was characterized by directed technical change focused on technologies which augmented Indian cotton.

6 Strong induced bias

This section explores the impact of a change in relative input supplies on relative input prices in the presence of directed technical change. My main focus will be on the relative price of Indian to lower quality U.S. cotton. I consider four hypothesis.

Hypothesis 1: The increase in the relative supply of Indian to U.S. cotton caused by the Civil War reduced the relative price of Indian cotton in the short run.

This hypothesis corresponds to the main short-run prediction of the theory. I will test this hypothesis by looking at the time path of the relative price of Indian cotton during the first two years of the war. The remaining three results are long-run results motivated by the evidence of directed technical change towards Indian cotton described in the previous section.

Hypothesis 2: Directed technical change towards Indian cotton had a positive effect on the relative price of Indian cotton.

This is a relatively weak hypothesis derived from Equation 2 in the model with N_I/N_{USL} allowed to vary. It can be tested by comparing the relative price of Indian cotton to that of Brazilian cotton or other varieties for which I did not find evidence of directed technical change. A stronger hypothesis is:

Hypothesis 3: Directed technical change toward Indian cotton offset the effect of the increase in relative supply such that the relative price of Indian cotton did not decrease even though it became relatively more abundant.

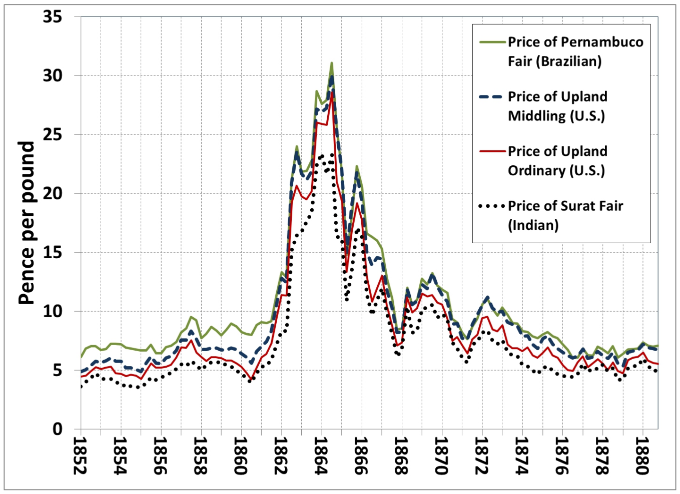
Finally, we have the strongest hypothesis:

Hypothesis 4: Directed technical change towards Indian cotton more than offset the effect of the increase in relative supply such that the relative price of Indian cotton increased even though it was relatively more abundant.

Hypothesis 3 corresponds to the prediction of the theory when $\sigma_l = 2$, while Hypothesis 4 corresponds to the prediction when $\sigma_l > 2$. Both of these can be evaluated by observing the time-path of the relative price of Indian cotton.

I begin my investigation by plotting, in Figure 8, the prices of Indian, Brazilian, higher-quality U.S., and lower-quality U.S. cotton in levels.[51] In all periods, these prices are roughly ordered according to quality, with Brazilian (Pernambuco) fetching the highest price, and Indian cotton the lowest. 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 the began to decline in 1866, though they did not attain their pre-war levels until well into the 1870s.

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



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

What we cannot see in the previous graph is the behavior of relative prices, which is our primary interest. These relative prices are presented in Figure 9, together

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[51] In keeping with the model, I will focus only on these four varieties. In the Appendix I show that the behavior of Egyptian cotton prices is similar to that of Brazilian.

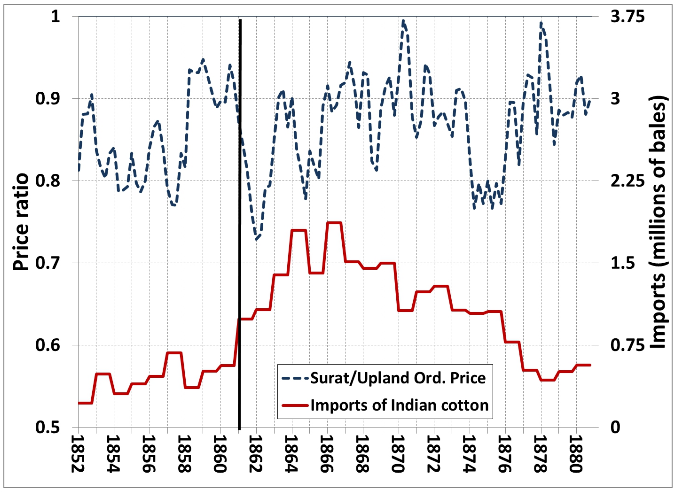
with the import quantities for each variety, where Indian and Brazilian cotton are each shown relative to the price of the most comparable U.S. variety. The price of Indian relative to lower-quality U.S. cotton was unusually low in 1861-1862, the first two years of the war, and a period in which Indian cotton had become relatively more abundant. However, starting in 1863, there was an increase in the relative price of Indian cotton. This upward trend lasted through the early 1870s, despite the fact that the relative quantity of Indian cotton remained higher than prior to 1861. In contrast, the relative price of Brazilian to U.S. cotton fell in 1861-1862 and remained low through the late 1870s, a period during which the relative abundance of Brazilian cotton was generally high. The patterns observed in Brazilian cotton prices is consistent with what the model would predict in the absence of significant biased technological progress, given the increase in the relative abundance of these varieties after 1861. In contrast, the initial decrease in the relative price of Indian cotton, followed by the increase after 1863, when a significant number of new technologies tailored to the use of Indian cotton were becoming available, is consistent with the strong induced-bias hypothesis.

One feature to note in these figures is that there is evidence of an increase in the relative price of Indian cotton in 1858, prior to the Civil War. This increase was due to the short-term effect of the Indian Mutiny (May 1857-1859) 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 reduction in supply had the expected short term 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.

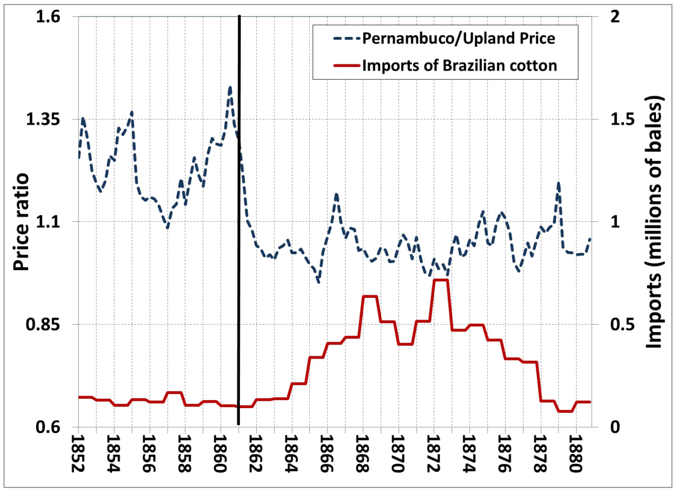
Figure 10 facilitates comparison between movements in the relative price of Indian and Brazilian cotton by plotting the log relative prices of Indian cotton and Brazilian cotton, with the mean value in 1852 set to one. We can see that the relative prices move within a similar range prior to 1861 (though they do not move together), and that they fall together in 1861, but these relative prices diverge after 1862, with Indian gaining relative to Brazilian. I argue that this divergence is due to the upward pressure on the relative price of Indian cotton exerted by increasing demand caused by the availability of better machines for processing Indian cotton. There is some evidence that the divergence persisted through 1880, suggesting that the new technologies may have had long-term effects.

Figure 9: Cotton prices relative to the benchmark U.S. variety and import quantities

Relative price of Indian cotton to lower quality U.S. cotton (Upland Ordinary)

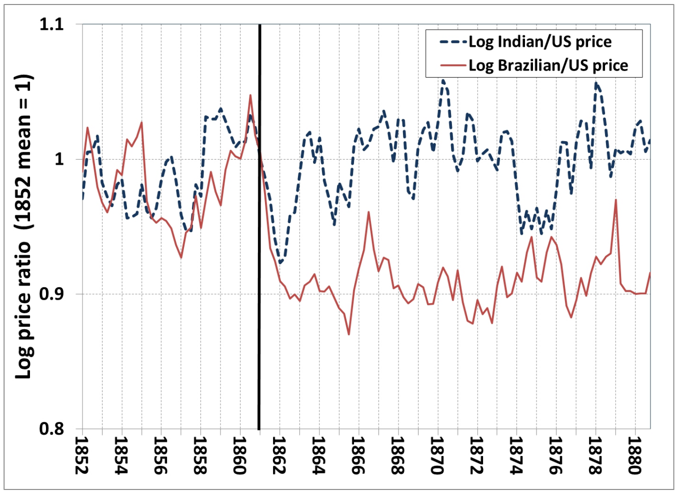


Relative price of Brazilian cotton to higher quality U.S. cotton (Upland Middling)



Price data gathered from *The Economist* magazine.

Figure 10: Comparing movement of relative Indian and Brazilian cotton prices



Price data gathered from The Economist magazine.

Constructing a statistical test of these hypothesis is made difficult by the non-linear nature of the predictions as well as uncertainty about the time-frame in which new technologies begin influencing the market. The main econometric approach I take to this problem involves pooling the relative price data from Indian and Brazilian cotton and using,

$$\log(RP_{lt}) = \alpha + \sum_{k=1861}^{1880} \beta^{I}_{lk} \times IN_l + \sum_{k=1861}^{1880} \beta^{B}_{lk} \times BR_l + IN_l + BR_l + \epsilon_{lt}$$

where l designates either Indian or Brazilian cotton, RP_{lt} is the price of the variety relative to the comparable U.S. variety, and IN_l and BR_l are indicator variables for Indian and Brazilian cotton, respectively. 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 of 1857-1858 on the relative price of Indian cotton. This equation is estimated using FGLS while allowing for correlation across panels, heteroskedasticity within panels, and AR1 serial correlation with serial correlation parameters specific to each panel.

The resulting coefficient estimates are shown graphically in Figure 11, while full regression results are available in the Appendix. The top panel shows the coefficient estimates and 95% confidence intervals when I do not include controls for the Indian Rebellion, while these controls are included in the regressions shown in the bottom panel. The sharp drop in relative prices for both varieties in 1861-1862 appears to confirm Hypothesis 1. Hypothesis 2 is also confirmed by Figure 11, since there is a clear gap between the 95% confidence intervals for the two varieties.[52] Figure 11 also confirms Hypothesis 3, since there is no evidence of a fall in the relative price of Indian cotton in the years after 1862, at least until 1874. Finally, Figure 11 offers some support for Hypothesis 4, since we observe positive coefficients for Indian cotton in most of the years from 1863 onward, with statistically significant increases in several years, particularly in the lower panel. While these results include only data for Indian and Brazilian cotton, Appendix A.6 shows that similar features emerge when Egyptian cotton is also included.

The results above provide evidence in favor of the strong induced-bias hypothesis operating for Indian cotton. There is no evidence that a similar effect occurred for Brazilian cotton. This makes sense given that I have observed technical change which was focused primarily on using Indian cotton.

In all of these results, I have compared Indian cotton to lower-quality U.S. cotton and Brazilian cotton to higher-quality U.S. cotton. One advantage of this is that it brings the analysis closer to the theory. Another advantage is that these results will be more robust to shift 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.

One potential caveat to this analysis is that the prices used are those on the Liverpool market, rather than farm-gate prices. Thus, they may reflect quality improvements in Indian cotton resulting from the new technologies which took place before the cotton reached the Liverpool market.[53] However, there are two reasons to think that this is not an important concern. First, the prices I use are for benchmark cotton varieties which are for a constant quality level, so quality improvements should not be reflected in these prices.[54] Second, using additional data described in

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[52] Wald tests confirm the statistical significance of the difference between the estimated coefficients for Indian and Brazilian cotton.

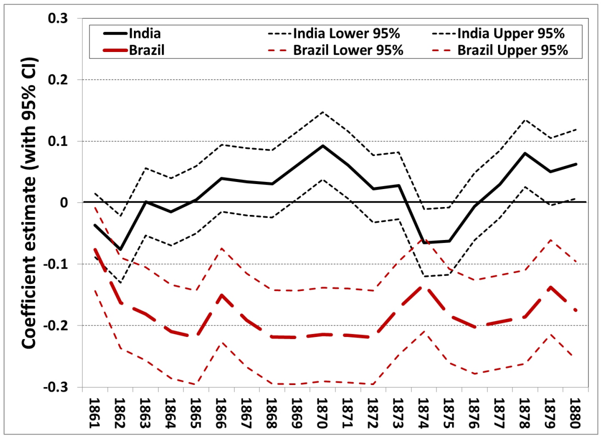
[53] The cotton could have benefited from processing by improved machines on its way from India, particularly since most ginning was done in the exporting country.

[54] Instead, quality improvements would be reflected in quantities shifting across the set of quality

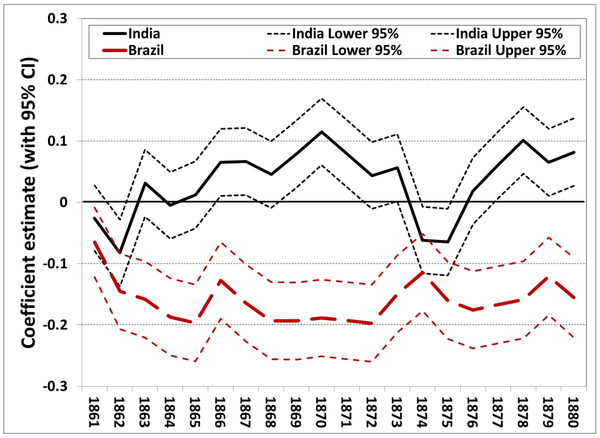
Appendix A.6, I show that changes in the Liverpool price of Indian cotton closely tracks the price in Bombay, the largest Indian export market, suggesting that there was no change in the gap between these prices induced by quality differences.

Figure 11: Estimated impact on the relative price of Indian and Brazilian cotton by year

Without controlling for effect of Indian Rebellion



With controls for Indian Rebellion



Estimated coefficients and 95% confidence intervals generated using FGLS regressions on quarterly data from 1852-1875. Standard errors are heteroskadasticity robust, allow for correlation across panels and AR1 serial correlation within panels with panel-specific serial correlation parameters.

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levels which, unfortunately, is not observable in the data.

7 Evaluating the theory

Can these patterns described in the previous two sections be explained by the theory? In order to answer this question, I need estimates of the elasticity of substitution between Indian and U.S. cotton. Using the model (Equation 2), the elasticity of substitution can be estimated by looking at the impact of short-run changes in relative supplies on relative prices. Rewriting this in regression form, I have (focusing on the low-quality market segment),

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

and the elasticity of substitution is $\sigma_l = -1/\beta_1$. However, in any regression of relative prices on relative quantities we will be worried about bias due to reverse causality. This is less of a concern in the current agricultural setting, since any major response of quantities to prices will be lagged by at least one year. However, I will still attempt to deal with this concern. We may also be concerned that there is autocorrelation in relative quantities. Given that relative technology levels are omitted in the regression specification above, and that directed technical change may be taking place, this raises a concern of omitted variable bias. One way to address both of these concerns is to use 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 vary only in the short-run, so that it does not affect relative technology levels.[55]

The instrument that I exploit is variation in the length of the cotton growing season in the U.S. The growing season length is number of days between first bloom and first frost, the dates of which are reported by the New York Times for 1837-1860.[56] Because these weather events are represent exogenous short-run fluctuations, they should satisfy the exclusion restrictions.[57] The two first-stage regressions that I use are,

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[55] 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.

[56] The New York Times report comes from October 8, 1866. I am grateful to Claudia Steinwender for making these data available to me.

[57] The length of the growing season does not exhibit a trend over time nor is there any evidence of autocorrelation.

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

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

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 7 for Indian/U.S. cotton.[58] 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 7 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 the top panel of Table 7 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 2.

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[58] Unfortunately it is not possible to generate similar results for Brazilian or Egyptian cotton using this approach. 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.

Table 7: 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 quantity	-0.0129	-0.00831	-0.00870	-0.0451	-0.0268
	(0.0302)	(0.0461)	(0.0483)	(0.0415)	(0.0429)
Time-trend			-0.00123		-0.000838
			(0.00260)		(0.00247)
Constant	-0.353***	-0.344***	-0.330***	-0.410***	-0.367***
	(0.0623)	(0.0747)	(0.0957)	(0.0745)	(0.0831)
Observations	23	23	23	23	23
	First-stage regression results				
Growing days		-0.0108**	-0.0109***		
		(0.0027)	(0.0021)		
Bloom date				0.0204***	0.01604**
				(0.0044)	(0.0057)
Frost date				-0.0067	-0.0086**
				(0.0036	(0.0035)
Time trend			0.0221		0.0149
			(0.0073)		(0.0094)
Constant		-0.1824	-0.4367	-2.9705*	-1.8586
		(0.4115)	(0.3522)	(1.2814)	(1.6016)
F-statistic		15.58	26.68	12.25	11.65
	Implied elasticity of substitution				
Estimate	77.52	120.38	114.9	22.2	37.34
Lower 95% C.I.	13.22	9.60	9.13	7.62	8.59

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

One potential source of bias in these results, relative to the theory, is due to the fact that I cannot separately identify the quantity or price of higher and lower-quality U.S. cotton. Thus, both quality levels are included in the data on U.S. cotton. As a result, the comparison between Indian and U.S. cotton includes both lower-quality U.S. cotton, which should be more substitutable with Indian cotton, and higher-quality U.S. cotton, which should be less substitutable with Indian cotton. This will bias the elasticity estimates shown in Table 7 downward compared to the elasticities of substitution that are relevant in the context of the theory, strengthening my finding that the elasticity of substitution between these cotton varieties was above 2.

Another potential source of bias suggested by the model is that some directed technical change may take place in response to the changes in input quantities generated by the weather shocks. Given the short-term nature of the weather shocks, this is unlikely. However, it is also possible to use the model to fully account for any potential bias due to directed technical change. If I make the extreme assumption that the model reaches the long-run relative technology level in each period, then the relationship between β_1 and σ_l is (from Equation 6) $\beta_1 = \sigma_l - 2$. Applying this extreme assumption to the estimates of β_1 I obtain alternative elasticity of substitution estimates which continue to be above 2. The corresponding 95% confidence bands stretch below 2 but are never below 1. Thus, the results are fairly robust to even this very extreme assumption about directed technical change.

One way to double-check these results is to compare them to results obtained using an alternative method based on the Almost Ideal Demand System (AIDS) introduced by Deaton & Muellbauer (1980). This method has previously been applied to the cotton textile industry by Irwin (2003). In Appendix 21, I show that estimates generated using this method also suggest an elasticity of substitution between Indian and U.S. cotton that is greater than 1 and also, in the most relevant cases, above 2.

8 Conclusions

One test of the generality of a model is to take it to a setting in which it could in principle apply, but which is far from the setting it was originally designed to explain, and see how it performs. This paper undertakes such a test for the directed technical change theory presented in Acemoglu (2002) using one such setting; I consider the impact of the U.S. Civil War on innovation in the British cotton textile industry.

The model performs well. Given my estimates for the elasticity of substitution between inputs, the model predicts that (1) technical change should be directed towards technologies which augment the input which had become relatively more abundant, (2) the relative price of the input which becomes more abundant should initially fall, and (3) the relative price of the input which becomes more abundant should rebound as the new technologies become available. In fact, I observe that the shortage of U.S. cotton during the U.S. Civil War led to directed technical change focused on technologies which augmented Indian cotton, which had become relatively more abundant. The relative price of Indian to U.S. cotton initially falls and Indian cotton became relatively more abundant, but it then rebounds two to three years into the war as the new technologies for working with Indian cotton were becoming available.

While I find evidence of directed technical change towards Indian cotton, I do not find similar evidence of innovation directed toward Brazilian or Egyptian cotton, which also became relatively more abundant during the Civil War period. One explanation for this, suggested by the theory, is that while incentives for innovation related to all of these may have increased, if these incentives increased more for Indian cotton then innovators should have focused, initially, on only that variety. Of course, other explanations are also likely; Indian cotton was initially larger, was able to respond more rapidly to the shortage of U.S. cotton, and may have faced clearer technological bottlenecks.

There is some evidence that the changes that occurred during the Civil War period might have had a longer-term impact on cotton production in India. The quantity of cotton exported from India remained much higher than in the pre-war period at least until the drought and famine of 1878-79. While U.S. cotton regained its dominance in the British market by the late 1870's, this was due in part to the diversion of Indian cotton directly to continental buyers as a result of the opening of the Suez canal in 1869. In addition to this export success, India's modern domestic cotton textile industry also experienced accelerated growth in the 1870s. Further work is needed to determine to what extent the technological changes generated by the Civil War contributed to these patterns.

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A Appendix

A.1 Further details on the empirical setting

A.1.1 Most innovative technology categories by patent count

Table 8: Top ten British Patent Office (BPO) tech. categories 1855-1883

Rank	Technology Category	No. Patents	Rank	Technology Category	No. 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 (fittings, etc.)	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.1.2 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 objects in combing are two, namely (1) to obtain the maximum parallelization of the fibers and (2) to remove impurities and undesired short fibers.

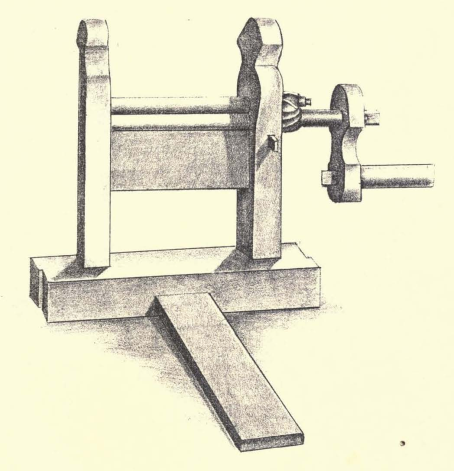
Gin- A cotton cleaning machine with the primary purpose of separating the cotton seeds from the cotton fibers.

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.

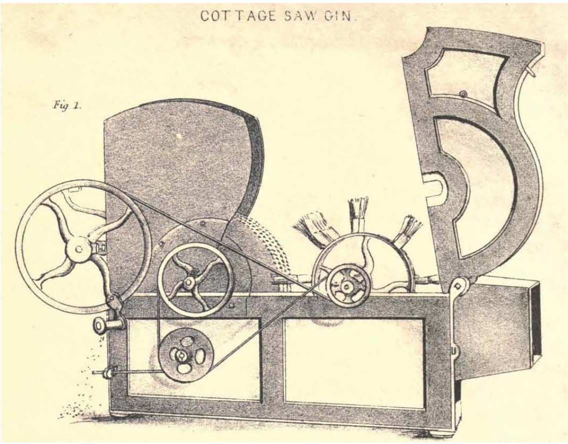
A.1.3 Machines for ginning cotton

Figure 12: Indian Churka for removing cotton seeds



Reproduced from Wheeler (1862).

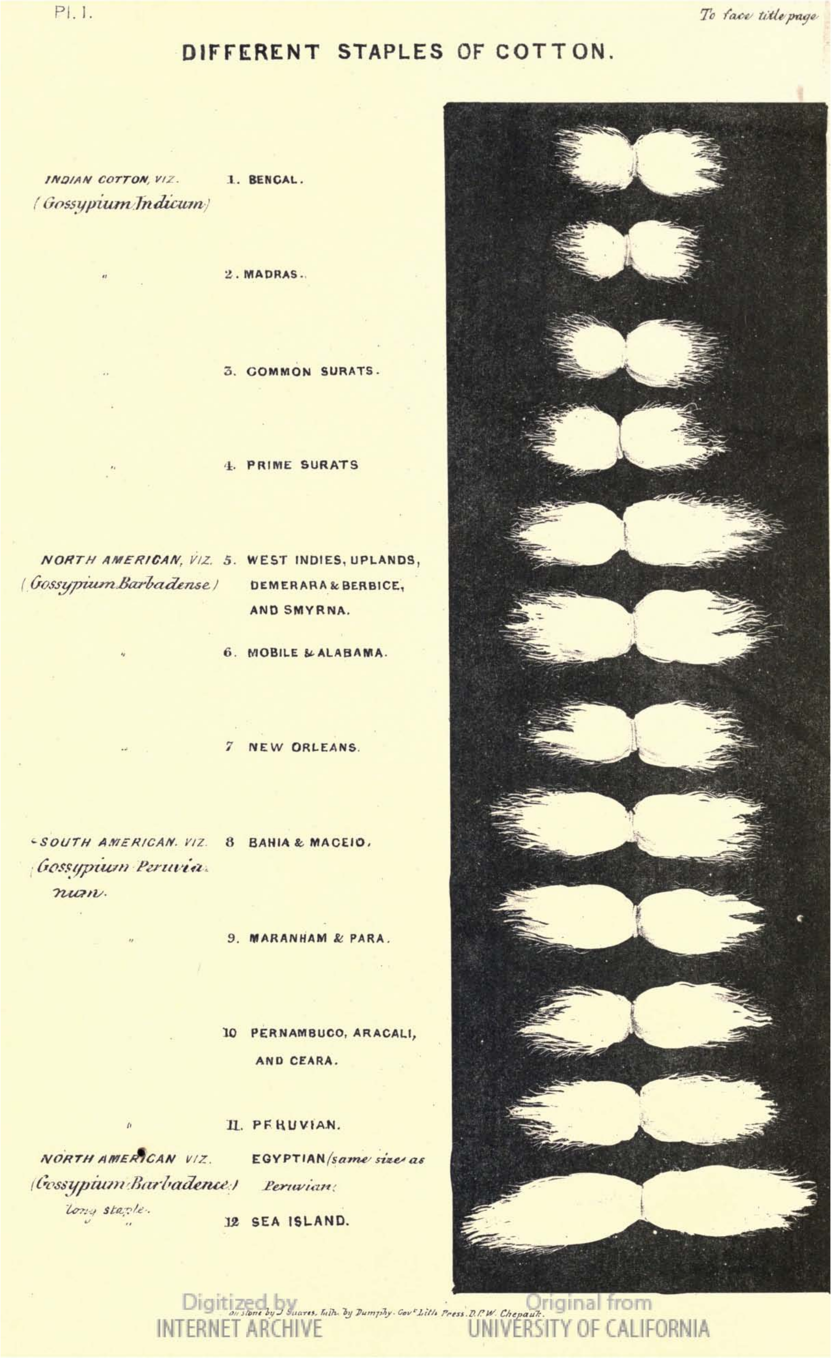
Figure 13: Cottage Saw Gin



Reproduced from Wheeler (1862).

A.1.4 Details on the differences between cotton types

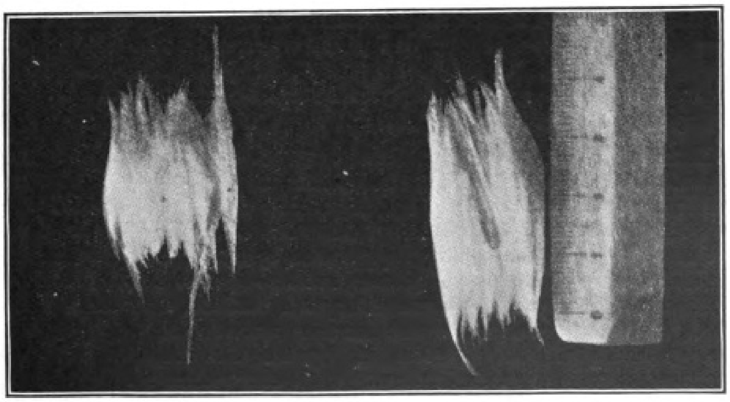
Figure 14: Length of cotton staples for various cotton types



Reproduced from Wheeler (1862).

A.1.5 Impact of ginning on cotton fiber length

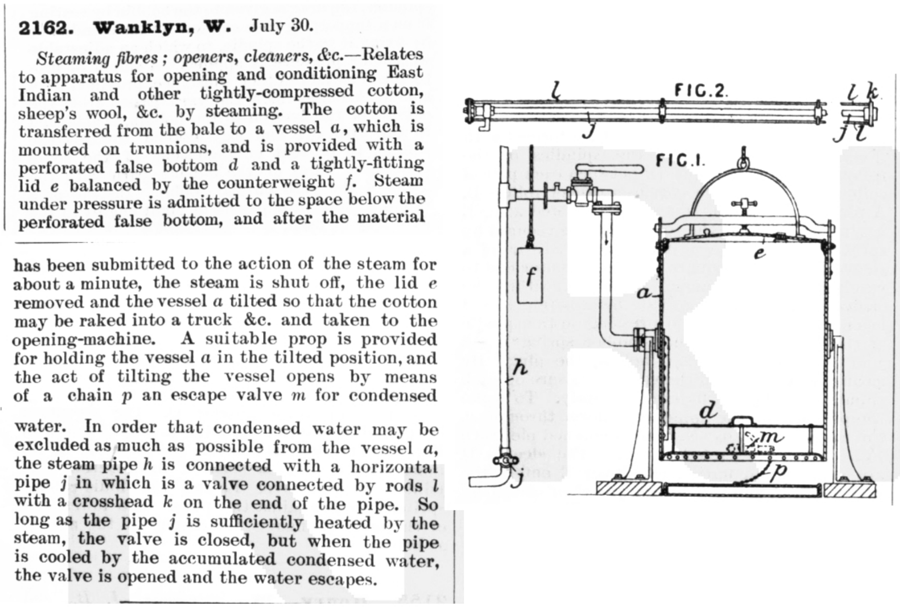
Figure 15: A comparison of ginned (left) and hand-cleaned cotton (right) fiber length



Reproduced from Pearse (1921).

A.1.6 Example patent specifically mentioning Indian cotton

Figure 16: An Example: Patent No. 2162 from 1862



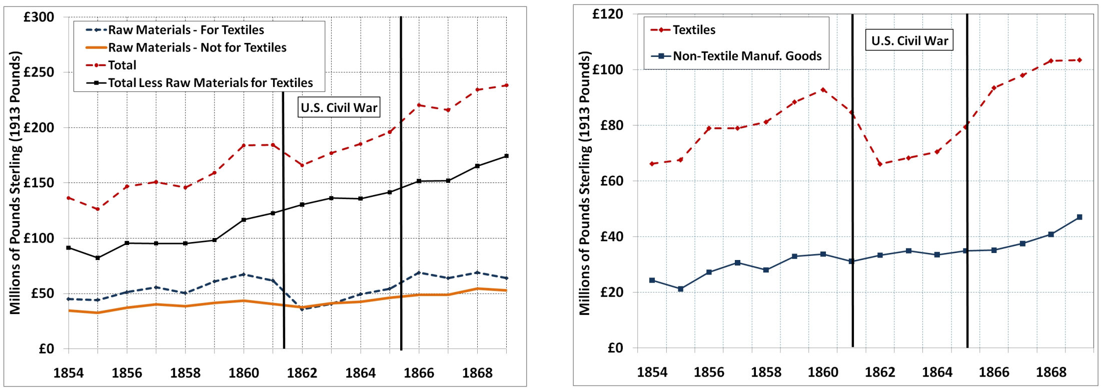
2162. Wanklyn, W. July 30.

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.1.7 Imports and exports

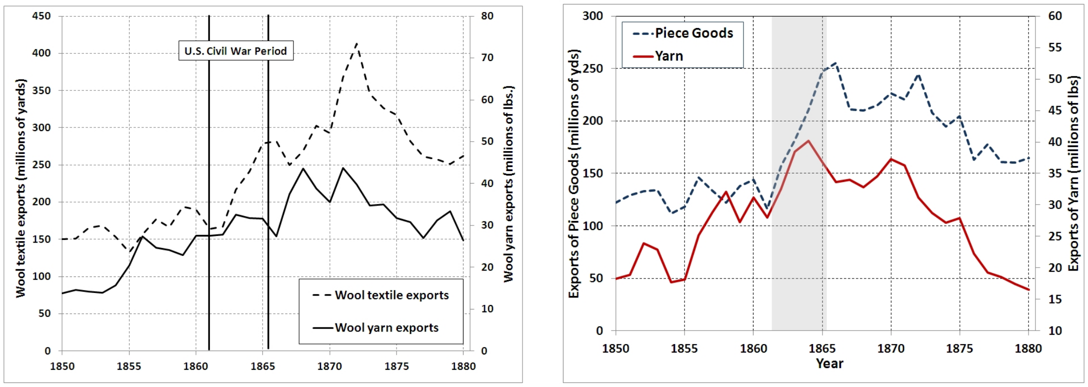
Figure 17: British imports and exports 1851-1869


British imports

British exports of finished manufactures

Data from Mitchell & Deane (1962).

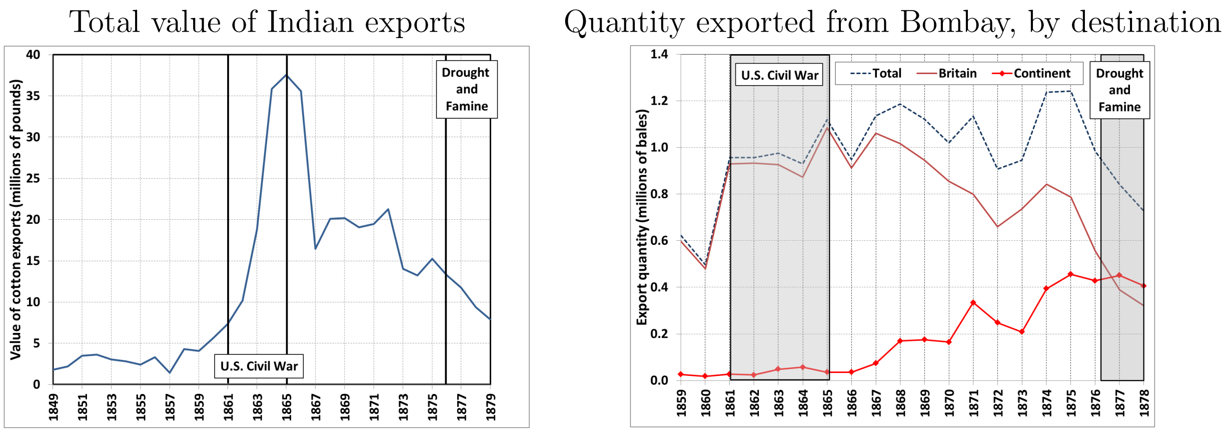
Figure 18: British wool and linen textile exports 1815-1910


Wool textile exports

Linen textile exports

Data from Mitchell & Deane (1962)

Figure 19: Indian cotton export charts



Export values from Statistical Abstracts of British India (UK Parliamentary papers. Export quantities for Bombay from Shepperson (1879).

A.2 Theory appendix

This appendix presents additional details related to the theoretical model.

A.2.1 Final-goods producers' optimization problem

The optimization problem for a final good producing firm in sector i in any period is,

$$\max_{\{x_i(k)\},Z_i} p_i \left(\frac{1}{1-\beta}\right)\left(\int_0^{N_i} x_i(k)^{1-\beta}dk\right) Z_i^{\beta} - c_i Z_i - \int_0^{N_i} \chi_i(k)x_i(k)dk\ .$$

The first-order conditions for this problem are,

$$x_i(k) = \left(\frac{p_i}{\chi_i(k)}\right)^{1/\beta} Z_i,$$

$$c_i = \left(\frac{1}{1-\beta}\right) p_i \left(\int_0^{N_i} x_i(k)^{1-\beta}dk\right) Z_i^{\beta-1}.$$

Using these and $\chi_i(k) = 1$ for all k (see main text) it is possible to use the machine price and machine demand expressions to rewrite production as a function of only the goods price, the level of technology and the input quantity:

$$y_i = \left(\frac{1}{1-\beta}\right) p_i^{\frac{1-\beta}{\beta}} N_i Z_i. \tag{10}$$

A.2.2 Results across market segments

To derive Equation 7 I begin by noting that the CES demand structure implies the following relationship between the price and quantity indices in the low and high-quality market segments:

$$\frac{P_L}{P_H} = \left(\frac{Y_L}{Y_H}\right)^{\frac{-1}{\epsilon}} . \tag{11}$$

I will substitute in for Y_L, Y_H, P_L, and P_H using the definitions for each of these terms given in the text. But first I want to write each of these price and quantity indices in terms of technologies and input quantities. Beginning with the price index for the low-quality market segment, I use $V_i = \beta p_i^{1/\beta} Z_i / r$ to write,

$$P_L = \left(\frac{r}{\beta}\right)^{\beta} V_I^{\beta} Z_I^{-\beta} \left[1 + \left(\frac{Z_{USL}}{Z_I}\right)^{-\beta(1-\rho_l)} \left(\frac{V_{USL}}{V_I}\right)^{\beta(1-\rho_l)}\right]^{\frac{1}{1-\rho_l}} .$$

A similar equation holds for the high-quality market segment. Taking the ratio of these, I have,

$$\frac{P_L}{P_H} = \left(\frac{V_I}{V_B}\right)^{\beta} \left(\frac{Z_I}{Z_B}\right)^{-\beta} \frac{\left[1 + \left(\frac{Z_{USL}}{Z_I}\right)^{-\beta(1-\rho_l)} \left(\frac{V_{USL}}{V_I}\right)^{\beta(1-\rho_l)}\right]^{\frac{1}{1-\rho_l}}}{\left[1 + \left(\frac{Z_{USH}}{Z_B}\right)^{-\beta(1-\rho_h)} \left(\frac{V_{USH}}{V_B}\right)^{\beta(1-\rho_h)}\right]^{\frac{1}{1-\rho_h}}} .$$

In the long-run balanced growth path it must be that $V_i/V_j = 1$ for all i and j and Equation 5 must hold. Using these, I have,

$$\frac{P_L}{P_H} = \left(\frac{Z_I}{Z_B}\right)^{-\beta} \frac{N_I^{\frac{-1}{1-\rho_l}}}{N_B^{\frac{-1}{1-\rho_h}}} \frac{[N_I + N_{USL}]^{\frac{1}{1-\rho_l}}}{[N_B + N_{USH}]^{\frac{1}{1-\rho_h}}} . \tag{12}$$

To solve for the relative quantity indices, I use, Equation 10 and $V_i = \beta p_i^{1/\beta} Z_i / r$ to write,

$$y_i = \frac{1}{1-\beta} \left(\frac{r}{\beta}\right)^{1-\beta} V_i^{1-\beta} Z_i^{\beta} N_i .$$

Plugging this into the low-quality market segment output index I obtain,

$$Y_L = \frac{1}{1-\beta}\left(\frac{r}{\beta}\right)^{1-\beta} V_I^{1-\beta} Z_I^{\beta} \left[N_I^{\frac{\rho_l-1}{\rho_l}} + N_{USL}^{\frac{\rho_l-1}{\rho_l}} \left(\frac{V_{USL}}{V_I}\right)^{\frac{(1-\beta)(\rho_l-1)}{\rho_l}} \left(\frac{Z_{USL}}{Z_I}\right)^{\frac{\beta(\rho_l-1)}{\rho_l}} \right]^{\frac{\rho_l}{\rho_l-1}}$$

A similar expression holds for the high-quality market segment. Taking the ratio of these, I obtain,

$$\frac{Y_L}{Y_H} = \left(\frac{V_I}{V_B}\right)^{1-\beta} \left(\frac{Z_I}{Z_B}\right)^{\beta} \frac{\left[N_I^{\frac{\rho_l-1}{\rho_l}} + N_{USL}^{\frac{\rho_l-1}{\rho_l}} \left(\frac{V_{USL}}{V_I}\right)^{\frac{(1-\beta)(\rho_l-1)}{\rho_l}} \left(\frac{Z_{USL}}{Z_I}\right)^{\frac{\beta(\rho_l-1)}{\rho_l}} \right]^{\frac{\rho_l}{\rho_l-1}}}{\left[N_B^{\frac{\rho_h-1}{\rho_h}} + N_{USH}^{\frac{\rho_h-1}{\rho_h}} \left(\frac{V_{USH}}{V_B}\right)^{\frac{(1-\beta)(\rho_h-1)}{\rho_h}} \left(\frac{Z_{USH}}{Z_B}\right)^{\frac{\beta(\rho_h-1)}{\rho_h}} \right]^{\frac{\rho_h}{\rho_h-1}}}$$

In the long-run balanced growth path, $V_i/V_j = 1$ for all i and j and Equation 5 holds. Using these, I have,

$$\frac{Y_L}{Y_H} = \left(\frac{Z_I}{Z_B}\right)^{\beta} \frac{N_I^{\frac{-1}{\rho_l-1}}}{N_B^{\frac{\rho_h-1}{\rho_h}}} \frac{\left[N_I + N_{USL}\right]^{\frac{\rho_l}{\rho_l-1}}}{\left[N_B + N_{USH}\right]^{\frac{\rho_h}{\rho_h-1}}} \tag{13}$$

Finally, I plug Equations 12 and 13 into Equation 11 and reorganize in order to obtain Equation 7.

A.3 Data appendix

A.3.1 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 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.3.2 Details of patent title search results

Summary statistics for these patent title search results are provided in Table 9. We can see that the majority of those patents listing one of the main textile inputs (cotton, wool, linen, silk) are classified into the BPO Preparatory & Spinning technology category, while a few are listed in the Weaving & Finishing category, and some others fall into categories other than those two. As a quality check, keyword searches were also used to identify those patents with "spinning" or "weaving' in the title. Most patents with spinning in the title are listed in the BPO Preparatory & Spinning category, while most of those mentioning weaving are classified in the BPO Weaving & Finishing category. This suggests that the keyword search approach is reliable, though more restrictive, than the BPO categories.

Table 9: Summary statistics from patent title keyword searches, 1855-1870

Title search term:	Total patents	Number in BPO Spinning	Share in BPO Spinning	Share of BPO Spinning	Number in BPO Weaving	Share in BPO Weaving	Share of BPO Weaving
Cotton	1,230	892	73%	29%	61	5%	2%
Wool	998	651	65%	21%	57	6%	2%
Linen	518	397	77%	13%	21	4%	1%
Silk	392	279	71%	9%	36	9%	1%
Spinning	976	935	96%	30%	25	3%	1%
Weaving	1,245	42	3%	1%	1,200	96%	46%

Patents are identified by searching for each title search term, e.g., "cotton", in the patent titles.

A.3.3 Details on inventors in the patent database

Table 10: 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.3.4 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.[59] 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.

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 foreign patent filings

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[59] 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).

I use patent data from India to assess whether the 1861-1865 period saw an increase in cotton and textile related patents which were widely applicable. This approach has been used previously by Lanjouw *et al.* (1998). The motivation behind this measure is that observing a British invention which was patented abroad indicates that the invention was viable in a wider range of circumstances.

The Indian patent data, which I gathered from original printed records, cover 1859-1879. During this period, 1,138 Indian patents were granted, of which 429 went to inventors based in Britain. Each Indian patent was manually reviewed in order to identify textile and cotton related technologies. Patents mentioning "cotton" in the title were coded as cotton patents, patents with "gin" in the title were coded as gins, etc. Most of these patents are either for cotton gins, or for balers and packers, which were used to prepare the cotton for shipping.

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. This approach has previously been used to value historical British patents by Nuvolari & Tartari (2011). These data 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.4 Appendix to directed technical change analysis

This section presents additional results related to the analysis of directed technical change. It begins with an econometric analysis of the impact of the shock on broad textile technology categories.

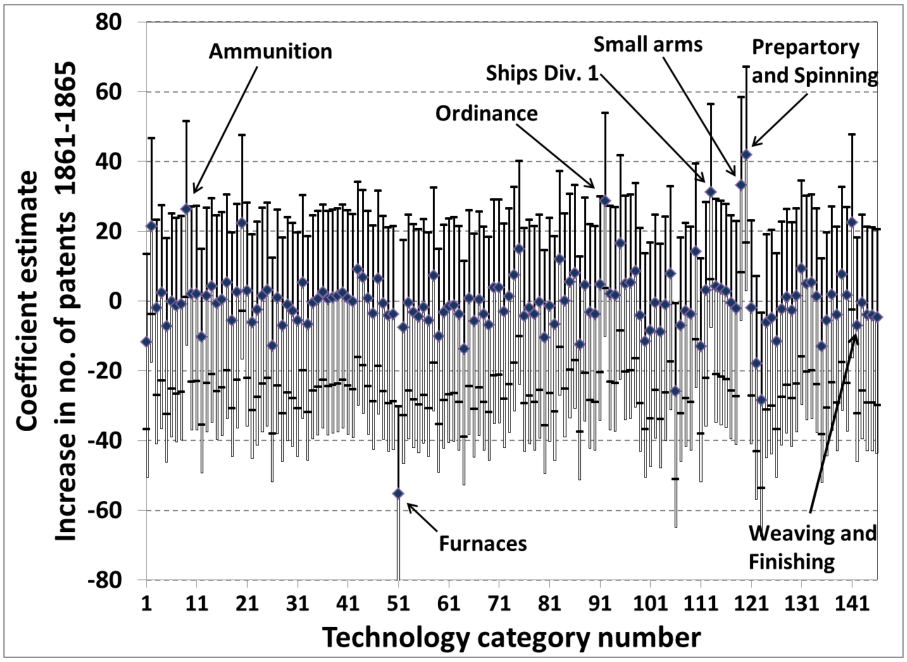
A.4.1 Regression results for the impact of the shock on overall cotton textile innovation

Figure 5 in the main text suggests that there was an increase in patents in the Preparatory and Spinning technology category during the Civil War period. I now investigate this pattern more rigorously. To do so, I pool data from all 146 BPO technology categories, indexed by c and run a regression based on,

$$P_{ct} = \left(\sum_{1}^{146} \gamma_c \times S_t \times I_c \right) + \Lambda_c + \xi_t + TT_{ct} + \epsilon_{ct},$$

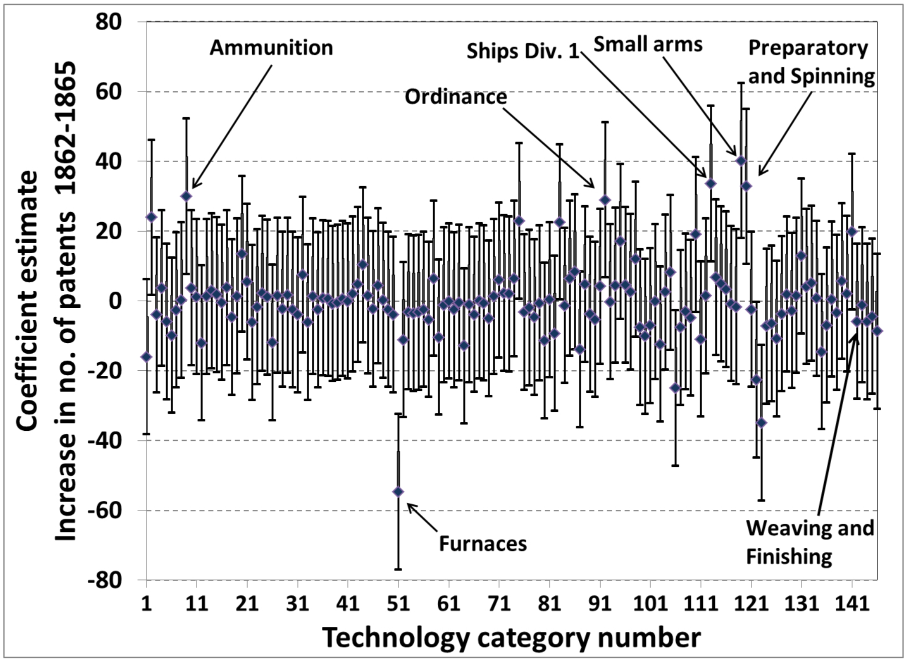
where P_{ct} is the count of patents in BPO technology category c in period t, S_t is an indicator variable for the shock period, I_c is an indicator variable for technology category c, Λ_c is a full set of category-specific indicator variables, ξ_t is a set of year indicator variables for all years outside of the shock period, and TT_{ct} is a full set of category-specific time-trend variables. I present the γ_c coefficient estimates graphically in Figure 20 where the shock period is 1861-1865. We can see that the Preparatory & Spinning technology category exhibits an increase in patents during the Civil War period. Interestingly, almost all of the other categories that experienced increases during this period are related to armaments. In Figure 21 I provide results from a similar regression in which 1861 is excluded from both the treatment and the control group. The coefficient estimate on the Preparatory & Spinning technology category remains one of the highest out of the 146 estimates. For consistency with the results presented in the main text, all of these regressions are done in levels with time-trends. However, similar results are obtained if I run the regressions in logs.

Figure 20: Coefficient estimates for impact of the Civil War on each BPO technology category



Coefficient estimates and 95% confidence intervals for each of the 146 BPO technology subcategories. Regression run using annual data from 1855-1883. Regression includes a fixed effect and time-trend for each technology category and a full set of year indicator variables.

Figure 21: Coefficient estimates for impact of the Civil War on each BPO technology category dropping 1861



Coefficient estimates and 95% confidence intervals for each of the 146 BPO technology subcategories. Regression run using annual data from 1855-1883. Regression includes a fixed effect and time-trend for each technology category and a full set of year indicator variables.

Next, I undertake a similar exercise looking across technologies related to each of the four main textile inputs: cotton, wool, linen, and silk. To do so, I pool the data four all four textile industries ($i \in \{Cotton, Wool, Linen, Silk\}$) and run a panel regression using,

$$P_{it} = \sum_{i=1 \in I} \gamma_i \times S_t \times I_i + \theta_i + \xi_t + TT_{it} + Q_t + \epsilon_{it},$$

where P_{it} is the count of patents in industry i and period t, S_t is an indicator variable for the shock period (Q2 1861 - Q1 1865), I_i is an indicator variable for industry i, θ_i is a full set of industry-specific fixed effects, TT_{it} is a full set of industry-specific time trends, ξ_t is a set of indicator variables for each year outside of the shock period, and Q_t is a set of quarter indicator variables (to control for seasonal effects). This regression is run on quarterly data from 1853-1870. Because these series contain more observations there are no quarter x industry bins with zero observations. Thus, I do not apply count data models in this setting. For consistency with the results presented in the main text, all of these regressions are done in levels, in some cases with time-trends. However, similar results are obtained if I run the regressions in logs.

Results are shown in Table 11. Columns 1-3 present results from a standard fixed effects regression. Columns 4-6 present results from FGLS regressions that are robust to heteroskedasticity, correlated errors across industries, and AR1 serial correlation with an industry-specific serial correlation parameter. All of these results suggest that there was an unusually high level of cotton textile patents during the Civil War period. Moreover, there is some indication that patents in other textile technologies fell during this period, though in general this result is not robust to the inclusion of the total of all non-textile patents as a control variable. Most likely this decrease was due to the financial crises that occurred in Northern England in the mid-1860's which may have affected innovation in many sectors.

Table 11: Panel-data regressions across textile industries

	FE regressions			**FGLS regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Cotton x Shock period	4.979***	6.739***	6.485***	4.529***	7.100***	6.553***
	(1.390)	(1.433)	(1.411)	(1.455)	(1.584)	(1.518)
Linen x Shock period	-4.098***	-2.068	-2.322	-4.499***	-1.811	-2.370**
	(1.390)	(1.433)	(1.411)	(1.285)	(1.126)	(1.047)
Silk x Shock period	-2.913**	-0.712	-0.966	-3.435***	-0.332	-0.871
	(1.390)	(1.433)	(1.411)	(1.279)	(1.087)	(1.059)
Wool x Shock period	-3.795***	-2.277	-2.532*	-4.312**	-1.954	-2.506
	(1.390)	(1.433)	(1.411)	(1.719)	(1.529)	(1.543)
Total non-textile patents			0.0165***			0.0187***
			(0.00512)			(0.00533)
Input TT (p value)		[0.0001]	[0.000]		[0.0001]	[0.000]
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288	288	288	288	288	288
Number of input_code	4	4	4	4	4	4

Regressions run on quarterly panel data from 1853-1870. FGLS standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include industry fixed effects, year effects, and quarter effects. Indicator variables for the first year and the first quarter are omitted. The shock period is Q1 1862- Q1 1865 and indicator variables for those years are omitted to avoid collinearity.

The results above include all patents mentioning cotton, wool, linen, or silk. The majority of these, but not all of them, are listed in the BPO's Preparatory & Spinning technology category. It is easy to conduct the same analysis on only those patents listed in the BPO's Preparatory & Spinning technology category, to see if the same patterns hold within this set, which is the most relevant for my study. Results are presented in Table 12. As we can see, the same results hold within the set of cotton, wool, linen, and silk patents listed in the Preparatory & Spinning technology category.

Table 12: Panel-data regressions across textile industries

	FE regressions			**FGLS regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Cotton x Shock period	4.745***	5.427***	4.450***	4.657***	5.575***	4.260***
	(1.185)	(1.234)	(1.051)	(1.795)	(1.816)	(1.422)
Linen x Shock period	-1.747	-1.155	-2.133**	-0.836	-0.106	-1.693*
	(1.185)	(1.234)	(1.051)	(1.033)	(1.089)	(0.869)
Silk x Shock period	-1.537	-0.876	-1.853*	-0.717	0.137	-1.508
	(1.185)	(1.234)	(1.051)	(0.922)	(0.958)	(0.950)
Wool x Shock period	-2.035*	-1.661	-2.639**	-1.447	-0.788	-2.317**
	(1.185)	(1.234)	(1.051)	(1.426)	(1.292)	(1.096)
Total non-textile patents			0.224***			0.202***
			(0.0235)			(0.0198)
Input TT (p value)		[0.0118]	[0.028]		[0.0004]	[0.002]
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288	288	288	288	288	288
Number of input_code	4	4	4	4	4	4

Regressions run on quarterly panel data from 1855-1870. FGLS standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include industry fixed effects, year effects, and quarter effects. Indicator variables for the first year and the first quarter are omitted. The shock period is Q1 1862- Q1 1865 and indicator variables for those years are omitted to avoid collinearity.

Next, I want to investigate more carefully the time path of the effect of the shock on innovation in the cotton textile industry. The key question here is whether the difference between what is happening in the cotton textile industry and other industries is driven entirely by patenting that occurred early in the Civil War period. If that were true, we might be concerned that these patterns were driven only by the patenting of existing ideas which became profitable as a result of the changes induced by the war, rather than the development of new innovations. To investigate this I use panel data on cotton, wool, linen, and silk technologies and use the following specification,

$$P_{it} = \sum_{j=1858}^{1868} \gamma_t \times YR_t \times COTTON_j + \phi_i + \xi_t + TT_{it} + Q_t + \epsilon_{it},$$

where YR_t is an indicator variable for year t and $COTTON_j$ is an indicator variable denoting the cotton textile industry. In this specification, ξ_t is a full set of year indicator variables. As in the previous table, I use both fixed effect and FGLS regressions. The results presented in Table 13 show that, while there was an immediate spike in patenting in 1861, there was also a relatively high level of patenting in cotton textile technologies later in the war, particularly in 1863-1864. Similar patterns emerge if I focus only on patents within the BPO's Preparatory & Spinning technology category.

Table 13: Timing of the response within the cotton textile industry

	FE regressions			**FGLS regressions**		
	(1)	(2)	(3)	(4)	(5)	(6)
Cotton x 1858	-2.262	-2.265	-2.265	-2.541*	-2.522*	-2.499*
	(2.369)	(2.350)	(2.305)	(1.475)	(1.470)	(1.476)
Cotton x 1859	-2.262	-2.262	-2.262	-2.642*	-2.586*	-2.626*
	(2.369)	(2.346)	(2.301)	(1.469)	(1.461)	(1.467)
Cotton x 1860	1.988	1.990	1.990	1.425	1.441	1.411
	(2.369)	(2.348)	(2.303)	(1.469)	(1.463)	(1.469)
Cotton x 1861	11.90***	11.91***	11.91***	11.72***	11.74***	11.71***
	(2.369)	(2.357)	(2.312)	(1.469)	(1.469)	(1.475)
Cotton x 1862	8.321***	8.329***	8.329***	8.197***	8.179***	8.142***
	(2.369)	(2.373)	(2.327)	(1.469)	(1.479)	(1.485)
Cotton x 1863	10.99***	11.00***	11.00***	10.02***	9.886***	9.928***
	(2.369)	(2.394)	(2.348)	(1.469)	(1.492)	(1.498)
Cotton x 1864	10.32***	10.33***	10.33***	10.51***	10.32***	10.33***
	(2.369)	(2.422)	(2.376)	(1.469)	(1.509)	(1.515)
Cotton x 1865	5.738**	5.753**	5.753**	5.669***	5.561***	5.538***
	(2.369)	(2.456)	(2.409)	(1.469)	(1.530)	(1.536)
Cotton x 1866	-0.512	-0.494	-0.494	-0.647	-0.830	-0.794
	(2.369)	(2.496)	(2.448)	(1.469)	(1.554)	(1.560)
Cotton x 1867	2.488	2.508	2.508	2.685*	2.406	2.434
	(2.369)	(2.541)	(2.492)	(1.469)	(1.580)	(1.587)
Cotton x 1868	0.155	0.177	0.177	-0.530	-0.854	-0.817
	(2.369)	(2.591)	(2.541)	(1.475)	(1.629)	(1.635)
Total non-textile patents			0.0166***			0.0172***
			(0.00504)			(0.00534)
Input TT (p value)		[0.0001]	[0.000]		[0.0000]	[0.0017]
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288	288	288	288	288	288
Number of input_code	4	4	4	4	4	4

Regressions run on quarterly panel data from 1853-1870. FGLS standard errors are robust to heteroskedasticity, correlation across panels, and AR1 serial correlation with panel-specific serial correlation parameters. All regressions include industry fixed effects, year effects, and quarter effects. Indicator variables for the first year and the first quarter are omitted. The shock period is Q1 1862-Q1 1865 and indicator variables for those years are omitted to avoid collinearity.

A.4.2 Durbin-Watson statistics for technology subcategories

This section presents Durbin-Watson statistics for the time series for each of the technology subcategories included in Table 2. To do so, I estimate the following time-series regressions for each technology subcategory:

$$P_t = \alpha + \beta\ S_t + \epsilon_t\ ,$$

$$P_t = \alpha + \beta\ S_t + TT_t + \epsilon_t\ ,$$

where P_t is the count of patents in period t in the technology subcategory, S_t is an indicator variable for the 1862-1865 period, and TT_t is a time-trend. Durbin-Watson statistics are then calculated on the residuals for each of these regressions. It is clear from these results that serial correlation is not a systematic issue in these data, particularly in the subcategories that I am most concerned with.

Table 14: Durbin-Watson statistics for technology subcategories

Subcategory	Without TT	With TT
Bearings	1.534	2.098
Carding	1.127	1.180
Combing	2.327	2.464
Finishing	2.118	2.181
Gins	2.369	2.365
Mules	1.223	1.353
Openers/Scutchers	1.671	1.678
Rollers	1.019	1.157

A.4.3 Subcategory Poisson regression results

In the main text Tables 2 and 4, Negative Binomial regressions were used to account for the discrete nature of the data. An popular alternative is to use Poisson regressions. In this section I present Poisson regressions analogous to those presented in the main text. These results show that the choice of which approach to use does not meaningfully affect the results. Table 15 presents Poisson regression results analogous to the Negative Binomial regression results in Table 2. Table 16 presents Poisson regression results analogous to those shown in Table 4

Table 15: Poisson panel-data regressions across textile technology subcategories

Dependent Variable: Number of patents	(1)	(2)	(3)
Bearings x Shock period	-0.571***	-0.649***	-0.486**
	(0.204)	(0.211)	(0.236)
Carding x Shock period	0.107	0.0288	0.107
	(0.0951)	(0.110)	(0.148)
Combing x Shock period	-0.105	-0.184	-0.102
	(0.143)	(0.153)	(0.183)
Finishing x Shock period	-0.323**	-0.401**	-0.367*
	(0.159)	(0.168)	(0.195)
Gins x Shock period	1.570***	1.491***	1.529***
	(0.181)	(0.189)	(0.217)
Mules x Shock period	0.0432	-0.0349	-0.0124
	(0.121)	(0.133)	(0.165)
Openers x Shock period	0.377***	0.299**	0.338**
	(0.128)	(0.139)	(0.171)
Rollers x Shock period	-0.305**	-0.384***	-0.300*
	(0.134)	(0.145)	(0.176)
Subcategory TT (p value)			[0.009]
Observations	176	176	176
Number of subcat_code	8	8	8

Regressions run on annual panel data from 1855-1876. All regressions include subcategory-specific fixed effects. Standard errors are shown in parenthesis.

Table 16: Poisson estimates of timing of effects on gins and openers/scutchers technologies

	(1)	(2)	(3)
Gins x 1858	0.606	0.871	0.980
	(0.540)	(0.551)	(0.635)
Gins x 1859	0.318	0.332	0.429
	(0.612)	(0.620)	(0.683)
Gins x 1860	-0.0870	0.00615	0.0923
	(0.736)	(0.743)	(0.786)
Gins x 1861	1.299***	1.169***	1.244***
	(0.408)	(0.418)	(0.477)
Gins x 1862	1.299***	1.230***	1.294***
	(0.408)	(0.419)	(0.464)
Gins x 1863	2.398***	2.321***	2.374***
	(0.289)	(0.303)	(0.348)
Gins x 1864	2.264***	2.445***	2.486***
	(0.299)	(0.316)	(0.347)
Gins x 1865	1.522***	2.123***	2.155***
	(0.376)	(0.397)	(0.413)
Gins x 1866	1.417***	1.380***	1.401***
	(0.391)	(0.402)	(0.411)
Gins x 1867	1.166***	1.316***	1.327***
	(0.430)	(0.442)	(0.445)
Gins x 1868	-0.0870	-0.202	-0.201
	(0.736)	(0.742)	(0.742)
Openers x 1858	-0.983**	-0.719	-0.949**
	(0.455)	(0.468)	(0.478)
Openers x 1859	-0.195	-0.182	-0.390
	(0.313)	(0.327)	(0.339)
Openers x 1860	-0.513	-0.420	-0.605
	(0.363)	(0.377)	(0.385)
Openers x 1861	0.352	0.222	0.0590
	(0.244)	(0.260)	(0.269)
Openers x 1862	0.809***	0.740***	0.600***
	(0.200)	(0.221)	(0.228)
Openers x 1863	0.740***	0.663***	0.546**
	(0.206)	(0.226)	(0.231)
Openers x 1864	-0.195	-0.0145	-0.108
	(0.313)	(0.330)	(0.331)
Openers x 1865	-0.108	0.493	0.423
	(0.300)	(0.326)	(0.327)
Openers x 1866	0.403*	0.366	0.320
	(0.238)	(0.256)	(0.257)
Openers x 1867	0.116	0.266	0.243
	(0.271)	(0.290)	(0.290)
Openers x 1868	0.626***	0.511**	0.513**
	(0.216)	(0.235)	(0.235)
Subcategory TT (p value)			[0.007]
Subcategory FEs	Yes	Yes	Yes
Year effects	No	Yes	Yes
Observations	176	176	176
Number of subcategories	8	8	8

Regressions run on annual panel data from 1855-1876. All regressions include subcategory-specific fixed effects. Standard errors are shown in parenthesis.

In the main text Table 5, I present Negative Binomial regressions in which I divide the patents by industry and technology subcategory. Here I present Poisson regressions results generated using the same basic specification.

Table 17: Subcategory x industry x shock period Poisson regression coefficient estimates

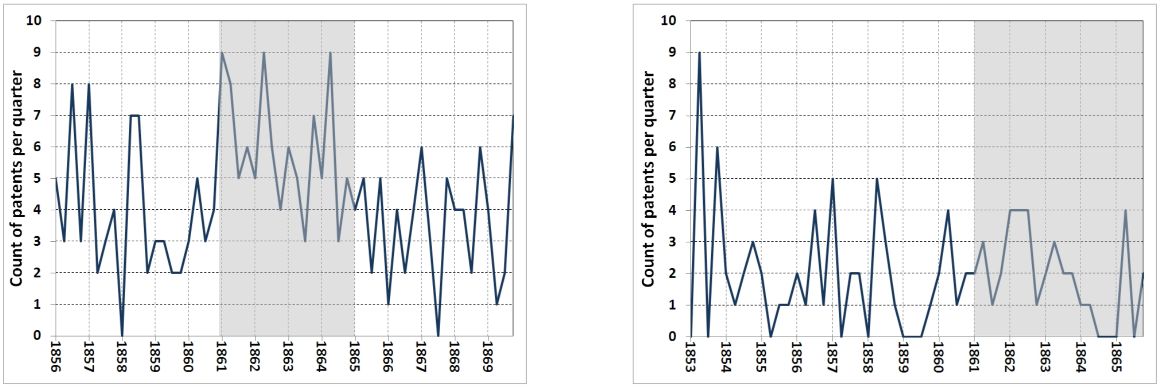
	Bearings	Carding	Combing	Finishing	Gins	Mules	Openers	Rollers
Cotton	-0.599*	-0.0296	-1.579***	-0.389	1.683***	0.151	0.366**	-0.432*
	(0.328)	(0.168)	(0.334)	(0.365)	(0.206)	(0.219)	(0.184)	(0.221)
Wool	-0.879**	-0.488**	0.133	-0.468	-1.358*	-0.844**	-0.694**	-0.762*
	(0.429)	(0.223)	(0.192)	(0.435)	(0.725)	(0.375)	(0.312)	(0.290)
Linen	-0.949	-0.926**	-0.330	-0.133	NA	-1.202*	-1.052*	-0.176
	(0.722)	(0.427)	(0.357)	(0.600)		(0.721)	(0.593)	(0.358)
Silk	-1.581	NA	-0.0187	1.314***	NA	-1.835*	-0.144	-1.213**
	(1.011)		(0.316)	(0.332)		(1.01)	(0.402)	(0.592)

Coefficient estimates are all from a single Poisson regression run on panel data with two cross-sectional dimensions (industries and subcategories). Annual data from 1855-1876. The shock period is defined as 1861-1865. Regression includes a full set of industry fixed effects, subcategory fixed effects, and year indicator variables. Negative Binomial regressions are warranted because the data are sparse, with 263 out of 704 subcategory x industry x year bins having zero patents.

A.4.4 Further evidence from the patent renewal fee data

This section provides some additional results using the data on the patents for which renewal fees were paid. I begin by graphing the renewal fee data for cotton and gins, openers, and scutchers. Recall that these dates represent the application data of patents which were subsequently renewed. We can see that there was a substantial increase in cotton patents and patents related to gins, openers, and scutchers, during the Civil War period, which were subsequently renewed at year three (left panels). For patents renewed at year seven (right panels), far fewer observations are available, but there is still evidence of an increase in gin, opener, and scutcher patents filed during the Civil War period for which a patent renewal fee was paid seven years later.

Figure 22: Cotton-related and gin/opener/scutcher technology patent renewals

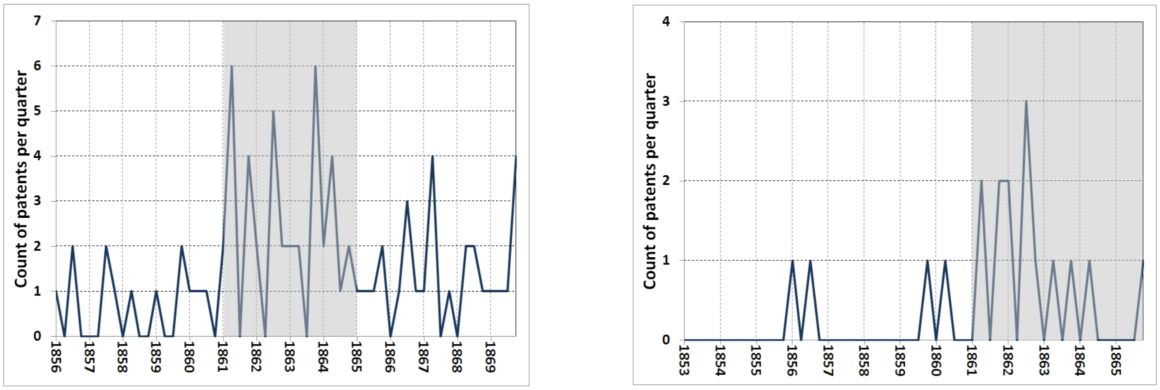


Cotton patents renewed at year three

Cotton patents renewed at year seven

Gin/opener/scutcher renewals at year three

Gin/opener/scutcher renewals at year seven



“At year three” indicates patents for which the renewal fee was paid in to keep the patent in force beyond year three. “At year seven” indicates that the renewal fee was paid to keep the patent in force beyond year seven.

Table 18 explores the impact of the Civil War on cotton patents econometrically. These regressions use panel data covering the four textile industries – cotton, wool, linen, and silk – for 1856-1869. Column 1-2 show results from a fixed effect regressions, without and with industry-specific time trends. Column 3-4 present results from FGLS regressions that allows for heteroskedasticity, correlated errors across industries, and AR1 serial correlation with industry-specific serial correlation parameters. Columns 5-6 present Poisson regression results (NegBin regressions failed to converge).

Table 18: Behavior of high-quality cotton patents during the Civil War period using renewal fee measure

	FE regressions		FGLS regressions		Poisson regressions	
	(1)	(2)	(3)	(4)	(5)	(6)
Cotton x	5.700**	5.751**	5.099**	5.307***	0.365**	0.337*
shock period	(2.116)	(2.140)	(2.173)	(2.006)	(0.177)	(0.181)
Year indicators	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry TTs	No	Yes	No	Yes	No	Yes
Observations	56	56	56	56	56	56

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full set of industry fixed-effects and year indicator variables.

A.5 Further evidence from the *Newton's London Journal* data

This section presents additional evidence generated using data on the patents mentioned in a contemporary periodical, *Newton's London Journal*. Table 19 presents results showing that there was also an increase in cotton-related technology patents filed during the 1862-1865 period for which abstracts appeared in *Newton's London Journal*. These regressions use panel data covering the four textile industries – cotton, wool, linen, and silk – for 1856-1869. Because I have relatively few observations for each industry, I do not include industry-specific time-trends. Column 1 shows results from a fixed effect regression. Column 2 presents results from an FGLS regression that allows for heteroskedasticity, correlated errors across industries, and AR1 serial correlation with industry-specific serial correlation parameters. Columns 3 presents Poisson regression results (NegBin regressions failed to converge).

Table 19: Behavior of high-quality cotton patents during the Civil War period using contemporary periodical measure

	FE regression	FGLS regression	Poisson regression
	(1)	(2)	(3)
Cotton x	5.792***	6.758***	0.386
shock period	(1.686)	(1.129)	(0.261)
Year indicators	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Observations	56	56	56

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full set of industry fixed-effects and year indicator variables.

A.5.1 Evidence from Indian patent data

Using the Indian patent data, I run some simple regressions to look at whether there was an increase in the share of these technologies in Indian patents, relative to all other technology types, during the Civil War period. I use the patent shares as the independent variable in these regressions so that the results are robust to factors that affected the overall propensity for inventors to patent in India. Because I do not observe patents related to other textile industries or to technology subcategories other than gins, these results, presented in Table 20, are based on time-series regressions with Newey-West standard errors to help control for serial correlation.

Table 20: Cotton textile technology patents in India during the Civil War

	Share of all Indian patents		**Share of patents by British inventors**	
	Cotton	Gins	Cotton	Gins
Shock Indicator	0.0442**	0.0249**	0.126**	0.0720**
(1861-1865)	(0.0173)	(0.0103)	(0.0515)	(0.0319)
Observations	23	23	23	23

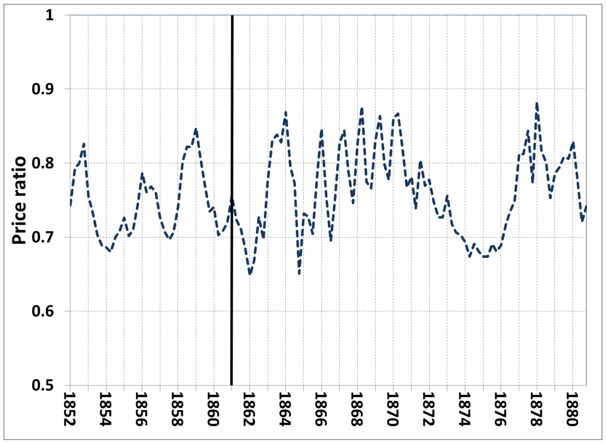
Table contains results from time-series regressions using annual data from 1856-1879. Standard errors are Newey-West with a lag length of 2. This approach assumes heteroskedastic standard errors while allowing for serial correlation up to a lag length of two.

A.6 Further evidence of strong induced bias

This section presents additional evidence related to the strong induced-bias results shown in Section 6. I begin by providing some additional graphs describing the movements of the prices of the various cotton varieties.

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

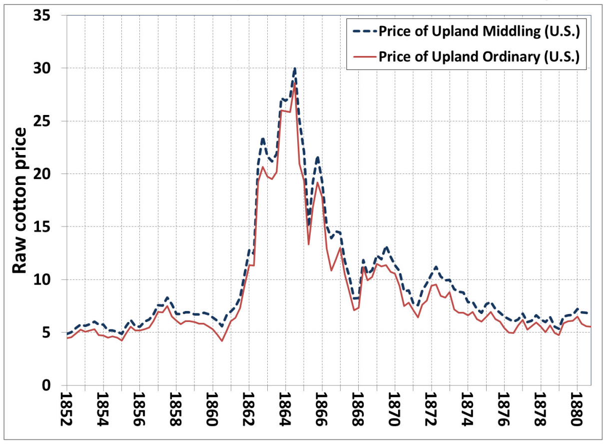


Data from The Economist.

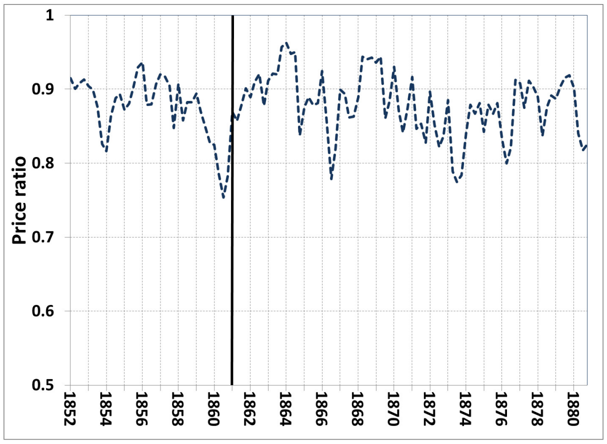
The next two graphs show that the relationship between the price of the higher and lower-quality U.S. cotton grades was essentially stable over the study period. The top graph show the prices of the two U.S. quality grades in levels, which the bottom graph shows the ratio of prices. We can see that the ratio is generally stable over the study period, with the potential exception of 1860, which was characterized by a short-lived drop in the relative price of lower to higher quality cotton.

Figure 24: Ratio of Indian / higher-quality U.S. cotton (Upland Middling)

Price of U.S. Upland Ordinary and Upland Middling cotton varieties



Ratio of U.S. Upland Ordinary / Upland Middling cotton prices



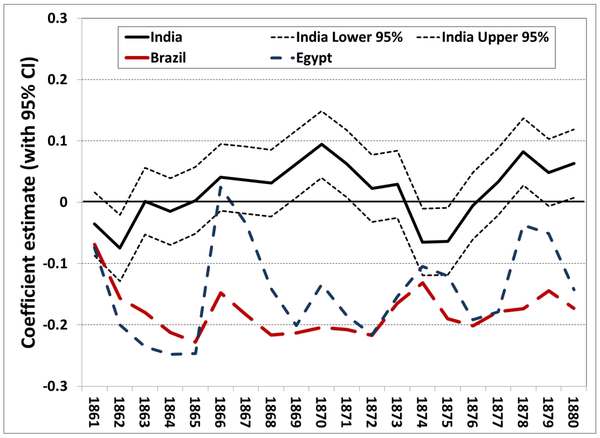
Data from The Economist.

A.7 Econometric results including Egypt

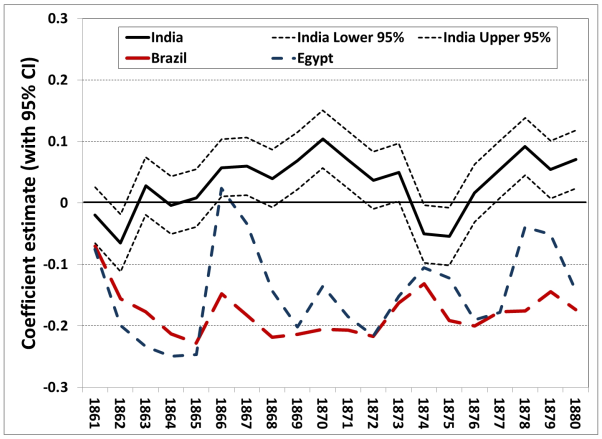
In Section 6 I investigate the behavior of relative prices after the onset of the Civil War pooling data from India and Brazil. Here I show that similar results hold if I also add data from Egypt. The graphs in Figure 25 mirror those shown in Table 11 except that they also display the estimated coefficients from Egyptian cotton. I have omitted the 95% confidence intervals for Brazilian and Egyptian cotton in order to make the graph readable.

Figure 25: Estimated impact on the relative price of Indian, Brazilian, and Egyptian cotton by year

Without controlling for effect of Indian Rebellion



With controls for Indian Rebellion

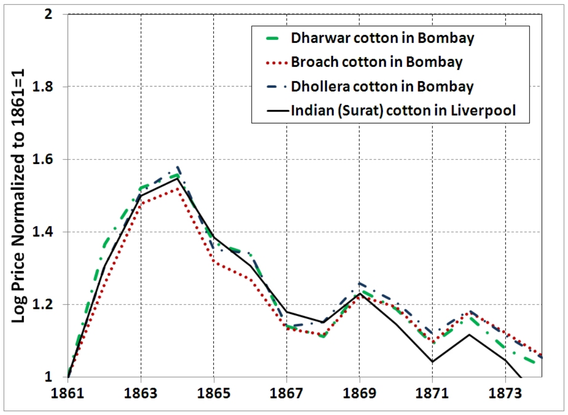


Estimated coefficients and 95% confidence intervals generated using FGLS regressions on quarterly data from 1852-1875. Standard errors are heteroskadasticity robust, allow for correlation across panels and AR1 serial correlation within panels with panel-specific serial correlation parameters.

A.7.1 Comparison of Bombay and London prices of Indian cotton

In this appendix, I look directly at cotton prices in Bombay in order to check if there appeared to be an increase in the gap between the Bombay and Liverpool prices of Indian cotton which would suggest that the prices were being influenced by quality improvements. While there is not a wealth of price data available, Atkinson (1897) does provide price indexes for three varieties of Indian cotton on the Bombay market. Figure 26 graphs these Bombay market prices together with the Liverpool market price, where all prices are presented in logs and normalized so that 1861=1. This is done to eliminate the need to compare in level terms, which is difficult given exchange rate fluctuations. We can see that these prices are moving together, which suggests that there were no quality improvements in the benchmark cotton varieties between the Bombay and London markets that could be affecting the price data used in Section 6.

Figure 26: Comparison of cotton prices on the Bombay and Liverpool markets



Liverpool price data gathered from *The Economist* magazine. Bombay price indices were constructed by Atkinson (1897).

A.8 Elasticity estimation appendix

This appendix contains details of the alternative elasticity estimates generated using the AIDS approach. 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. Later, I will discuss the direction of bias introduced by combining different types of 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 and so I drop the equation for Egyptian cotton, the fourth largest variety.

Table 21 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 21 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 21: 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. Full regression results are available in the appendix. 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.

The results shown in Table 21 are likely to suffer from three sources of bias. First, the AIDS approach assumes that export supplies are perfectly elastic. In fact, the supply curves for these varieties are clearly upward sloping. Ignoring this will bias the elasticity estimates downwards. Second, the estimates in Table 21 were generated while pooling higher and lower-quality U.S. cotton. Yet the relevant elasticity of substitution for evaluating the theory is between Indian and lower-quality U.S. cotton (or Brazilian and higher-quality U.S. cotton). Since these are more similar varieties, the elasticities of substitution that are relevant for the theory must be higher than those shown in Table 21. Finally, these estimates ignore the possibility of directed technical change. From Acemoglu (2002), we know that regardless of the elasticity of substitution, an increase in the relative supply of one input generates technical change that act to increase the price of that input. Thus, if directed technical change is taking place, this will bias the estimated elasticities of substitution shown in Table 21 upwards. Of the sources of bias present in the AIDS estimates, the most troubling is the potential bias due to directed technical change, which may cause the estimates in Table 21 to overstate the true short-run elasticities of substitution.