Industry Connections and the Geographic Location of Economic Activity*

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Abstract

This paper provides causal evidence that inter-industry connections can influence the geographic location of economic activity. To do so, it takes advantage of a large, exogenous, temporary, and industry-specific shock to the 19th century British economy. The shock was caused by the U.S. Civil War, which sharply reduced raw cotton supplies to Britain’s important cotton textile industry, causing a four year recession in the industry. The impact of the shock on towns in Lancashire County, the center of Britain’s cotton textile industry, is compared to towns in neighboring Yorkshire County, where wool textiles dominated. The results suggest that this trade shock reduced employment and employment growth in industries related to the cotton textile industry, in towns that were more severely impacted by the shock, relative to less affected towns. The impact still appears over two decades after the end of the U.S. Civil War. This suggests that temporary shocks, acting through inter-industry connections, can have long-term impacts on the distribution of industrial activity across locations.

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1 Introduction

Marshall (1890) suggested that firms in different industries may benefit from locating near to one another, through localized inter-industry spillovers. He identified three channels through which these benefits could flow: input-output linkages, labor market pooling, or technology spillovers. Since then, inter-industry spillovers have been incorporated into theories of industrial linkages and development (Hirschman (1958), Ciccone (2007)), industrial clusters (Porter (1990)), the benefits of urban economies (Jacobs (1969)), the benefits of trade and FDI (Young (1991), Rodríguez-Clare (1996)), and the geography of economic activity (Krugman & Venables (1995)). Policy makers, too, have been influenced by these ideas. The existence of inter-industry spillovers is one of the prime motivations for local industrial policies, such as the tax incentives offered to firms by U.S. municipalities, or the widespread use of special industrial zones in developing countries. The cost of these policies can run into the hundreds of millions of dollars for single U.S. municipalities.\footnote{See Greenstone & Moretti (2004).}

Despite this interest, and widespread application, empirical evidence on the role of inter-industry connections in influencing the geographic location of economic activity is sparse. This is due largely to the difficulty of measuring the patterns of connections between industries, though these measures are improving.\footnote{There are a number of early studies which looked for the impact of inter-industry connections without accounting for the patterns that these connections take. Important contributions include Glaeser et al. (1992), Kim (1995), Henderson (1997), and Henderson (2003). There is also a much larger literature considering the role of spillovers within industries.} In an important recent study, Greenstone et al. (2010) show evidence of localized productivity spillovers between plants that share similar labor or technology pools.\footnote{Another interesting contribution is Bloom et al. (2007).} In a similar vein, Javorcik (2004) finds evidence of spillovers from FDI firms to upstream suppliers.\footnote{Similar evidence is also provided by Kugler (2006), Poole (2009), and Balsvik (Forthcoming).} More related to the current study is Ellison et al. (2010), which uses measures of input-output connections, labor force similarity, and technological spillovers, to provide evidence that the underlying pattern of connections between industries is influencing the geographic location of industries. While these are important contributions, they do not address the most relevant question for policy: can temporary changes in the local availability of inter-industry spillovers, such as those created by economic shocks or policy interventions, have long-term impacts on the geographic location of economic activity?

This study takes the next step, by utilizing a large temporary external shock that altered the spillovers available to certain industries in certain locations, in order to provide causal evidence that changes in the availability of inter-industry spillovers can influence
the long-run distribution of economic activity. The shock was caused by the U.S. Civil War and impacted the British economy in the 1860s. During the 19th century, cotton textile production was the largest British manufacturing industry, and cotton textiles were Britain’s largest export. This industry relied entirely on imports of raw cotton, a vital input. Prior to the onset of the U.S. Civil War in 1861, the majority of raw cotton came from the Southern U.S., but the war, and the corresponding Union blockade of Southern ports, sharply reduced raw cotton supplies. The result was a four year depression in the industry, lasting from roughly 1861-1865. Our focus will be on how this affected the location of those industries related to (sharing spillovers with) the cotton textile industry.

As with other studies using historical examples (e.g., Donaldson (2010)), the event considered in this study was chosen because it has features that are particularly helpful in identifying the effects of interest, which are unlikely to be found in similar modern events. First, the shock was large, exogenous, and temporary. While the cotton shortage reduced production by about half during the shock period, the cotton textile industry rebounded quickly, attaining its original growth path by roughly 1866-67, only a year or two after the end of the war. Second, the direct effects of the shock were largely industry-specific. British import and export data suggest that, once cotton textiles are removed, the shock had no major effect on other British manufacturing sectors. Thus, changes observed in those industries related to cotton textiles can be attributed to the shock, transmitted through inter-industry connections. Third, despite the large magnitude of the negative effects of the cotton shortage, there was virtually no government intervention. This was largely due to the very strong free-market ideology that was dominant in Britain at the time, particularly in the northern industrial districts that were hardest hit by the recession.

A final important feature is that some locations were severely impacted, while other, economically similar locations, were left nearly untouched. This study compares outcomes in towns from two industrial counties in the north of England, Lancashire and Yorkshire. Lancashire was the heart of Britain’s cotton textile industry at the time. Yorkshire, lying just to the east, was similar to Lancashire in many ways. The key difference between these two counties was that, while towns in Yorkshire also had large textile industries, Yorkshire producers focused primarily on wool-based textiles (woollens & worsted) rather than cotton. Thus, while towns in Lancashire were severely affected by the cotton shortage, towns in Yorkshire were not negatively impacted. Comparing industry growth rates from towns in these two counties thus allows us to better identify the impact of the shock.

The basic hypothesis that we test is that the shock negatively affected employment and employment growth in industries more closely related to the cotton textile industry, in locations more severely impacted by the shock, by reducing the spillover benefits available to these industries. Importantly, we focus on impacts occurring in the years and decades after
the Civil War had ended and the cotton textile industry had rebounded. The hypothesis
is motivated by a two-country dynamic Ricardian trade model building on work by Young
(1991) and Matsuyama (1992). In the model, technology growth is driven by localized
learning-by-doing spillovers within and between industries. A negative shock to one industry
reduces the spillover benefits enjoyed by related industries, in the location in which the
affected industry is concentrated. The result is a reduction in technology growth in the
related industry, in the more severely affected location relative to the less affected location.
Moreover, the model describes channels through which a loss of spillovers in one period
can affect employment and employment growth in related industries in future periods. The
model is used to derive the empirical specification used in the analysis.

This intuition is perhaps best illustrated using an example from the empirical setting,
provided by the Engine & Machinery industry (E&M). This was an important industry in
Britain at this time, and one that was connected to the cotton textile industry in Lancashire,
as well as the wool textile industry in Yorkshire, through all three of Marshall’s channels. In
fact, Marshall himself used the textile and engineering industries to illustrate the possibility
of labor market pooling benefits. There is also evidence suggesting that textile machine
makers learned from the nearby textile producers that they supplied. Engine and machine
makers in Lancashire and Yorkshire competed, both to supply customers in these locations,
as well as in the important export market. The data show that the E&M industry had a
similar growth path in the two locations prior to the shock, but that E&M firms in York-
shire towns gained an advantage relative to Lancashire producers in the following decades,
allowing them to expand employment more rapidly. This suggests that the recession in the
cotton textile industry had persistent impacts on distribution of the E&M industry across
locations.

The empirical strategy used to test this hypothesis involves using panel data with two
cross-sectional dimension, allowing us to compare impacts across time (pre vs. post shock
periods), locations (towns with higher vs. lower shock intensity), and industries (more vs.
less related to cotton textiles). The primary data are drawn from the British Census of
Production, which were gathered from original sources. These data provide employment
disaggregated into 171 industry groups, spanning nearly the entire private sector economy,
available for every ten years from 1851-1891. Thus, we have multiple observations in both
the pre- and post-shock period, and are able to observe effects up to 25 years after the end
of the recession. These data are available for 11 principal towns, 6 in Lancashire, and 5 in
Yorkshire, providing the geographic dimension of the analysis. Additional data from local
Poor Law boards, which were the primary source of funds for unemployed workers during
this period, allow us to measure the severity of the shock in each town. We find that the

\footnote{Marshall (1920) (p. 226).}
share of cotton textiles in a town’s employment in 1851 is a good predictor of the severity of the shock in each location. Thus we are able to strengthen our identification strategy by using each town’s cotton textile employment in 1851 as an instrument for shock intensity.

An important input into the analysis is a measure of the pattern of connections between the cotton textile industry and other industries. Two measures are used. The first is based on the degree to which each industry is geographically coagglomerated with the cotton textile industry, following work by Ellison & Glaeser (1997). Ellison et al. (2010) show that this measure is related to measures of input-output linkages, labor market pooling potential, and technology spillovers. The second measure is an intermediate goods input-output matrix based on Thomas (1987).

The results suggest that industries more closely related to the cotton textile industry, based on the geographic coagglomeration measure, suffered lower employment and employment growth, in more severely affected towns, in the post shock period. The impacts are estimated while controlling for aggregate industry-level and town-level shocks in each year, as well as time-invariant industry-location factors. The impact of the shock on employment and employment growth continues to appear through the 1881-1891 period. The implication is that inter-industry connections can play an important role in affecting the geographic location of economic activity across locations. Moreover, temporary changes in the availability of these connections appear to have the potential to generate long-lasting effects. There appear to be no persistent effects related to the intermediate goods input-output matrix, suggesting that the observed effects are being driven by other types of inter-industry connections.

This project is related to three additional strands of literature. On set of related literature studies whether temporary shocks have long-term impacts on the geographic location of economic activity, in order to test economic geography models which predict multiple equilibria in the location of economic activity. Most studies focus on the impact of temporary shocks caused by war on city size. Only two studies consider the impact on the location of industries, and these deliver mixed results. This study improves on previous work by (1) considering the role of industry connections and (2) using data that are more

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7Davis & Weinstein (2002), Brakman et al. (2004), Bosker et al. (2007), Bosker et al. (2008b), and Bosker et al. (2008a). In related work, Miguel & Roland (2006) consider the impact of bombing in Vietnam on welfare outcomes.
8Davis & Weinstein (2008) study the effect of the WWII bombing of Japanese cities on the location of eight highly aggregated industrial sectors (e.g., machinery, metals) and find no evidence of persistent effects. In contrast, Redding et al. (forthcoming) study the impact of the division of Germany following WWII on one particular industry, airport hubs, and find evidence of a persistent effect.
detailed and comprehensive. The results of this study are consistent with the existence of multiple equilibria in the geographic location of economic activity, providing support for economic geography models predicting multiple equilibria.

Second, because this project considers the impact of a large temporary trade shock on industry growth over a relatively long time frame, it can help inform our understanding of the relationship between trade and growth. While there is a large empirical literature studying the overall relationship between trade and growth, there are relatively few studies considering the impacts of temporary trade shocks. The contribution of this study is to show that temporary trade shocks can have long-term economic impacts. Moreover, while we have focused on two regions with a country, in order to better identify the effects of interest, our results raise the possibility that trade shocks may also result in reallocations of industries across countries, which could have long-term impacts on country growth rates and the gains from trade. This suggests that a complete understanding of the relationship between trade and growth should take into account the potential effects of increased (or decreased) susceptibility to trade shocks, in addition to the more direct effects of increased overall trade.

Finally, because we study the textile industry in 19th century Britain, there is a natural connection to the debate over the sources of the Industrial Revolution. In particular, there is disagreement over the importance of trade in generating British economic growth. The results of this study support the view, due to Allen (2009) and others, that trade propelled technological progress in the engineering and machinery industries, primary drivers of the industrial revolution, through their connections with the large textile industries.

The next section provides background information on the empirical setting and describes the shock, while Section 3 describes the data used. Section 4 studies the impact on one industry, Engine & Machine manufacturing. Section 5 introduces a model that is used to guide the econometric analysis, which is presented in Section 6. Section 7 concludes.

9For example, this study considers 171 industry groups, while Davis & Weinstein (2008) consider only eight aggregated industrial sectors and Redding et al. (forthcoming) consider only one, airport hubs.
10See Rodriguez & Rodrik (2000) for a review and critique of recent macroeconomic literature on trade and growth.
11Recent work by di Giovanni & Levchenko (2009) suggests that trade liberalization may increase volatility in an economy.
12Authors such as Deane & Cole (1967) and Rostow (1960) emphasized that trade, by generating the demand which allowed the expansion of the cotton textile industry, was a key “engine of growth”. Mokyr (1985) (p. 22) and McCloskey (1994) (p. 255-258) have disputed this view, arguing that trade, while helpful, did not drive productivity growth, and that gains from trade were relatively small.
13Among the most related industries to cotton textiles, based on the geographic coagglomeration measure, are “Engineering and Machinery”, “Millwrights”, and “Iron and Steel”. This argument is made for industrialization more generally by Ciccone (2002).
2 Empirical setting

Lancashire County, in the Northwest of England, was the heart of the British cotton textile industry from the end of the 18th century and the cradle of the Industrial Revolution. For the purposes of this study, Cheshire, a smaller cotton textile producing county just south of Lancashire, is treated as part of Lancashire. Lancashire’s main commercial city, Manchester, became synonymous with the cotton textile trade, and the main port, Liverpool, served as the center of the world’s raw cotton market. Yorkshire, the large and historically important county just east of Lancashire had followed Lancashire’s lead in industrialization and was similar to Lancashire in many respects. This study focuses only on the West Riding area of Yorkshire, which is the main industrial area of the county. Figure 1 shows the location of these counties in England (left panel) and highlights the principal towns (right panel), over which the analysis will be conducted. Figure 2 shows that, while Lancashire was somewhat larger than Yorkshire during the study period, the two counties followed similar population growth paths and had relatively similar industrial structures.

Figure 1: Maps of the study area

\[\text{Map of English Counties in 1851} \quad \text{Map of Northwestern England and the West Riding}\]

\[14\text{This practice is common for historians studying Yorkshire during this period, because it separates the more modern industrial area of the West Riding from the less developed economies of the North and East Riding.}\]
However, there was one key difference between Lancashire and Yorkshire. While Lancashire produced cotton textiles, producers in Yorkshire concentrated on wool textile goods (woollen and worsted), industries with a long history in the area. Table 1 describes total private employment, and employment in the cotton and woollen/worsted industries in Lancashire and Yorkshire, in 1851, the beginning of the study period. We see that cotton textile employment made up over 29% of private sector employment in Lancashire, but only 4% in Yorkshire, while woollen/worsted employment made up 1% of private sector employment in Lancashire but over 30% of employment in Yorkshire.15

![Figure 2: Population and Occupation Comparisons - 1851-1891](image)

**Working population trends - 1851-1891**

**Log industry emp. share - 1851**

Author’s calculations based on British Census of Population data.

<table>
<thead>
<tr>
<th></th>
<th>Lancashire</th>
<th>Yorkshire</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Workers</td>
<td>1,052,154</td>
<td>574,820</td>
</tr>
<tr>
<td>Cotton Textile Workers</td>
<td>308,243</td>
<td>23,116</td>
</tr>
<tr>
<td>(as pct. of total workers)</td>
<td>29.30 %</td>
<td>4.02 %</td>
</tr>
<tr>
<td>Wool Textile Workers</td>
<td>11,354</td>
<td>174,556</td>
</tr>
<tr>
<td>(as pct. of total workers)</td>
<td>1.08 %</td>
<td>30.37 %</td>
</tr>
</tbody>
</table>

* Lancashire values include Cheshire
** Yorkshire values are for the West Riding only

15 In 1861, just before the onset of the shock, 85% of cotton textile manufacturing workers in England and Wales were located in Lancashire, while 72% of all of the woollen textile manufacturing workers, and 90% of worsted textile workers, were located in Yorkshire.
Despite using different input materials, the cotton and woollen/worsted textile industries were largely similar. For instance, they shared the same three basic production stages. Stage one involved spinning the raw input into yarn. In the second stage, yarn was woven into fabric, while in the final stage the fabric was finished, which often included bleaching, dyeing, and printing. As a result of this similarity, many technologies developed for one of the industries were also adapted to work in the other. For example, spinning and weaving machines first developed for cotton were modified for use in wool and other textile production. Moreover, as these industries had grown to prominence, first for cotton in Lancashire and later for woollen/worsted in Yorkshire, a large number of subsidiary trades had grown up around them. These related industries included textile machinery producers, chemical manufacturers to produce dyes and bleaches, engineering firms to produce the steam engines that powered the plants, and other textile industries that took advantage of the technological innovations made in the cotton textile industry.

2.1 Impact of the U.S. Civil War

Prior to 1861, most of the raw cotton used in England’s textile mills was grown in the Southern U.S. The onset of the U.S. Civil War in 1861 created a major disruption of raw cotton supplies. While other major suppliers, such as India and Egypt, did increase production, they were unable to adjust rapidly enough to make up for the sharp fall in U.S. exports. Raw cotton prices responded to the tightening of supply by rising. The left-hand panel of Figure 3 shows a dramatic spike in cotton prices starting in 1861 and continuing through 1865. Notably, the price increase in 1861 was actually fairly small. J.C. Ollerenshaw (1870, p.112), remarked in his presentation to the Manchester Statistical Society, that, “The American War commenced on April 5th, 1861, but for many months it had little effect on commerce - being generally regarded as merely temporary...” This reflects the commonly held belief that the U.S. Civil War was going to be short and cause relatively little disruption to economic activity. Margins also suffered during the period, with margins on spun cotton yarn becoming negative in 1862 and not recovering pre-shock levels until 1866. In response to the curtailment of supply, rising prices, and falling margins, production in the cotton

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18 A figure showing this drop is available in the Appendix.
19 Furthermore, the cotton produced by these other suppliers, India in particular, was often of a shorter fiber variety that was an imperfect substitute for the high quality long-fiber U.S. cotton. Often, producers were required to mix more expensive American cotton with the Indian cotton in order to make it strong enough to spin. Thus, the fall in imports is likely to understate the impact of the shock on cotton supplies. See Henderson (1969) (pp. 50-51).
20 Data from Forwood (1870). See also, Helm (1869).
textile industry fell. One of the best indicators of output in the industry is raw cotton consumption, described in the right-hand panel of Figure 3. To summarize, the onset of the U.S. Civil War reduced cotton imports, increased prices, and decreased output. The effects started in 1861, peaked in 1862-3, and persisted through 1865.\textsuperscript{21} Figure 3 also shows that by the late 1860s, the cotton textile industry had returned to its original growth path. Its expansion then continued with only relatively minor interruptions until WWI.\textsuperscript{22} The recovery of production in the cotton textile industry is an important feature of the story, because it suggests that any long-term effect that the shock had on related industries had its roots in the shock period, rather than in persistent changes to the cotton textile industry.\textsuperscript{23}

To argue that the U.S. Civil War created a shock that was primarily industry-specific, we look for evidence of other large direct effects of the war. We would expect any such effects to occur either through import or export channels. However, British import data from Mitchell (1988) suggest that, once raw material for textiles are removed, British imports show no noticeable effect from the U.S. Civil War. Similarly, once textile exports are excluded, British exports also show no negative effects.\textsuperscript{24} We may be particularly concerned that the areas we study were directly affected by the U.S. Civil War through armament industries. However, none of the three armaments categories included in our data, “Guns”, “Ordinance”, and “Ships”, make up more than 0.2% of employment in any of towns included in this study, during the study period, with the exception Liverpool, which is not included in the analysis for this reason.\textsuperscript{25}

\textsuperscript{21}Ollerenshaw (1870) stated that, “...we may consider 1862-5 as the years during which the effect of the American war were really experienced,” adding later that, “The year 1866 is to be regarded as an exceptional year [for cotton manufacturers], equally with 1861. The war was over but prices had fallen only 1d to 1.5d per lb.”

\textsuperscript{22}Lazonick (1990) p. 138.

\textsuperscript{23}It is worth noting that the impact of the cotton shortage on manufacturers and traders in cotton textiles was more complex than it appears from the foregoing graphs. A number of manufacturers and traders made enormous profits at the beginning of the shock period, by selling stocks of cotton goods or raw cotton at much higher prices. However, later in the shock period manufacturers often found their resources severely strained (See Henderson (1969) (pp. 19-20)). For the rest of England, the early 1860s was generally a period of prosperity, though there were financial crises in 1864 and 1866 as a result of a decline in English gold reserves. This loss of reserves was due in part to a switch from purchasing raw cotton from American in exchange for manufactured goods to purchasing from India, Egypt, or Brazil, where goods were generally purchased with gold or silver. Importantly though, these financial crises affected England as a whole, and should therefore not generated differential impacts between Lancashire and Yorkshire, except to the extent that Lancashire banks and firms were more vulnerable due to the effects of the shock. The late 1860s, on the other hand, was a period of poor economic performance throughout England, with numerous bankruptcies among financial, commercial, railway, and manufacturing firms, a hangover from the earlier financial crises.

\textsuperscript{24}Graphs of British import and export data are available in the Appendix.

\textsuperscript{25}Shipbuilding made up roughly 2-4% of employment in Liverpool during the study period, and Liverpool was active in providing ships used in the Civil War.
Unlike cotton, the woollen and worsted industries show little effect from the shock.\footnote{Data from Mitchell & Deane (1962).} It is not surprising that imports of raw wool are unaffected, since most of these imports come from Spain, Australia, South Africa, or South America. While there was some effect on wool textile exports to the U.S., this was made up for by an increase in exports to European markets during the period, particularly to France following a new trade agreement in 1860, and through increased demand for military woolens.\footnote{Helm (1869) states, “in some of our foreign markets, linen and woolen goods have, as at home, taken the place of cotton.” See also Jenkins & Ponting (1987) (p. 157-163) for a broad discussion of the effect of the U.S. Civil War on wool and worsted textiles. While the U.S. imposed an additional tariff on wool textile imports under The Morrill Tariff Act of 1861, wool textile exports to the United States rose steadily during the 1860’s (Jenkins & Ponting (1987) p. 157-163) due to weak competition from domestic suppliers and the need for heavy woolen goods for military uniforms and supplies.}

Given that we observe a strong negative shock to the cotton textile industry but little direct effect on the woollen and worsted industries, we should expect the direct effects to be much stronger in Lancashire than in Yorkshire. This is confirmed by Figure 4, which shows the number of able-bodied workers seeking relief from local Poor Law Boards as a fraction of the total 1861 population, in Lancashire and Yorkshire, over the shock period.\footnote{Data are drawn from several of the major districts within each county, but do not cover the entire county.} These Poor Law Boards were the main apparatus through which relief was provided to paupers and the unemployed in England during this period.\footnote{Southall (1991) shows that Lancashire had the highest rate of pauperage of any English county in 1863, with 10.3 percent of the population receiving Poor Law Relief, while the West Riding was among the lowest.}
To summarize, while the U.S. Civil War generated an enormous negative shock to cotton textiles, a shock that fell heavily on Lancashire, it appears that other direct effects on the British economy were of limited size. In contrast to the experience of Lancashire, Yorkshire’s mainstay wool textile industry shows little effect from the shock, and may have actually benefited somewhat from substitution away from higher priced cotton textiles. It is this large differential impact that is exploited in this study in order to pinpoint the effects of the shock on those industries that were related to cotton textiles.

Figure 4: Able-bodied relief seekers as a share of 1861 population

Data from Southall et al. (1998).

3 Data

The primary database used in this study is drawn from the British Census of Population. These decennial Censuses are the best available source of information on the structure of the British economy over the period of this study, 1851-1891.\textsuperscript{30} For each census, occupation data was collected from respondents by trained registrars, and each census report presents summaries of employment by occupational category.\textsuperscript{31} The number of occupational categories in these reports varies somewhat over the period studied, with a high of 478 categories in 1861 and a low of 348 in 1891.

\textsuperscript{30}See Lee (1979) p. 3.

\textsuperscript{31}Woolard (1999) compares these summary tables to the original enumerators books from the Isle of Man in 1881 and finds that “the original process of classification was remarkably accurate in light of the rules applied” (p. 29), particularly in the manufacturing and industrial categories.
One feature of these occupational categories is that they generally closely correspond to industries. For example, there are occupational categories such as “Cotton textile manufacturer”, “Chair maker”, and “Nail manufacture”. This feature allows us to treat occupational categories as industries. Over the four decades covered by this study, some adjustments were made to the reported occupational categories. Linking these categories over time was a time-consuming task that eventually yielded occupations gathered into 234 occupational groups (hereafter, just “groups” or “industries”) of which 204 groups are available for all years. Of these, 171 private sector occupational categories are used in the analysis.

Data are available at three levels of geographic specificity. The most specific is the town level, for towns with populations over 50,000. Our main analysis takes advantage of 11 towns for which consistent data can be obtained for 1851-1891. Six of these towns are located in Lancashire and five are in Yorkshire. Data are also available at the district level. These districts are larger than towns and data is available for the entire area of the two counties, but only for 1851-1861. Data are also available at the county level.

The towns used in our analysis are listed in Table 2, together with town population, a measure of the intensity of the shock in each location based on the increase in relief seekers as a share of the 1861 population, and the share of cotton textile employment in each town in 1851. Our primary measure of the severity of the shock in each town will be the percentage point increase in able-bodied workers seeking relief over the shock period, based on data from local Poor Law Boards, shown in the fourth column of Table 2. We will also want to apply an instrument for the shock severity measure, for reasons discussed later. The instrument will be the share of cotton textile employment in total employment in each town in 1851, which are shown in the last column of Table 2.

Table 2 reveals significant variation in cotton employment and the intensity of the shock across towns. Even within Lancashire, there is variation in the impact of the shock, despite the fact that all towns were major cotton textile centers. Contemporary reports suggest that some of this variation was due to local specialization in different product categories (e.g., heavy vs. fine cotton fabrics) or stages of the production process (e.g., spinning vs.

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32 Scholars familiar with these data have noted that it is nearly impossible to perfectly match occupational categories over time due to changes in occupational classifications (see, e.g., Lee (1979)). Even within the aggregated industry groups that were constructed for this project, it is sometimes not the case that employment values are comparable over time. However, the differences-in-differences approach used in this study relies on comparisons across locations within years, so the results should be robust to most changes in occupational classifications.

33 These 171 industries exclude 6 cotton based industries as well as government occupations and occupations that do not correspond to industries, such as “Labourer”.

34 Details related to the construction of the database are available in the Appendix.

35 A map showing the location of these towns is available in Appendix.
weaving), which were impacted differently by the shortage of raw cotton. Still, a casual glance at the last two columns Table 2 suggests that those towns in which cotton textiles made up a significant share of production in 1851 tend to have experienced a more intense shock effect. This relationship can also be tested more formally; regression results are presented in Table 3. These results indicate that 1851 cotton textile employment share will be a strong instrument for the severity of the shock in each town.

Table 2: Towns used in the analysis

<table>
<thead>
<tr>
<th>County</th>
<th>Town</th>
<th>1861 Pop.</th>
<th>Increase in relief seekers/1861 pop.</th>
<th>Cotton emp. /1851 pop.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lancashire</td>
<td>Blackburn</td>
<td>63,126</td>
<td>7.75%</td>
<td>34.00%</td>
</tr>
<tr>
<td></td>
<td>Bolton</td>
<td>70,395</td>
<td>1.55%</td>
<td>22.59%</td>
</tr>
<tr>
<td></td>
<td>Manchester</td>
<td>460,428</td>
<td>8.96%</td>
<td>11.63%</td>
</tr>
<tr>
<td></td>
<td>Oldham</td>
<td>94,344</td>
<td>3.59%</td>
<td>5.01%</td>
</tr>
<tr>
<td></td>
<td>Preston</td>
<td>82,985</td>
<td>9.39%</td>
<td>25.12%</td>
</tr>
<tr>
<td></td>
<td>Stockport*</td>
<td>54,681</td>
<td>3.70%</td>
<td>12.63%</td>
</tr>
<tr>
<td>Yorkshire</td>
<td>Bradford</td>
<td>106,218</td>
<td>-0.12%</td>
<td>0.58%</td>
</tr>
<tr>
<td></td>
<td>Halifax</td>
<td>37,014</td>
<td>0.29%</td>
<td>0.71%</td>
</tr>
<tr>
<td></td>
<td>Huddersfield</td>
<td>34,877</td>
<td>0.32%</td>
<td>1.28%</td>
</tr>
<tr>
<td></td>
<td>Leeds</td>
<td>207,165</td>
<td>0.34%</td>
<td>0.06%</td>
</tr>
<tr>
<td></td>
<td>Sheffield</td>
<td>185,172</td>
<td>0.85%</td>
<td>0.04%</td>
</tr>
</tbody>
</table>

* Stockport, Cheshire is treated as part of Lancashire in this study
Poor Law relief data from Southall et al. (1998).

Table 3: Relationship between cotton textile employment and shock intensity

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shock intensity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(incr. in relief seekers/1861 pop.)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cotton tex. emp. shr. 1861</td>
<td>0.728**</td>
<td>(0.228)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cotton tex. emp. shr. 1851</td>
<td>0.714**</td>
<td>(0.234)</td>
</tr>
<tr>
<td>Constant</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.530</td>
<td>0.509</td>
</tr>
</tbody>
</table>

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

36See Arnold (1864) (p. 102) and Henderson (1969) (p. 2). A map showing the distribution of cotton textile manufacturing activities across Lancashire towns is available in the Appendix.
While the data set spans 171 industries and 11 towns, not all industries have positive employment in all towns in all years. Because we work with log employment, location-industries with no employment will result in missing entries. For the analysis, we will include only location-industries that have positive employment levels for all five years. The result will be an unbalanced panel with 1,543 complete location-industries. In essence, this analysis will be on the intensive margin of employment, i.e., changes in employment levels in industries present in a location, while ignoring the extensive margin, i.e., industries emerging or disappearing in a location. This makes sense given that our focus is on the role of inter-industry spillovers, which presumably exist primarily when both industries are present in a location.

### 3.1 Industry relatedness

One important input into the analysis is a measure of relatedness between the cotton textile industry and other industries in the economy. Two approaches are taken to measuring the pattern of relatedness. The first uses the British Census data to construct a relatedness measure based on the geographic coagglomeration of industries. This measure is inspired by Ellison & Glaeser (1997), as well as, Ellison et al. (2010), who find that geographic coagglomeration patterns are correlated with measures of technological spillovers, occupational similarity, and input-output flows.\(^{37}\) Thus, the advantage of this measure is that it may reflect many forms of relatedness, though this comes at the cost of not being able to identify the particular types of industry connections that matter the most. Geographic coagglomeration is measured for each pair of industries and reflects the propensity of the two industries to concentrate production in the same location, where concentration implies that the size of the industry is in excess of the size that would be predicted given the location’s overall size (population). Specifics of the calculation of the coagglomeration measure are available in the Appendix.

It is important to note that the geographic coagglomeration measure is calculated using the district level census data, which are different from the town-level data used as the primary outcome variable. The district-level data are significantly more geographically comprehensive than the town-level data, giving us more regions to work with (71 districts vs. 11 towns). Furthermore, we can calculated an alternative coagglomeration dropping all of the districts containing towns available in the town-level data and show that this alternative coagglomeration measure delivers similar results.

---

\(^{37}\)One critique of this approach is Helsley & Strange (2010), who show that coagglomeration patterns across locations may be inefficient. This should, if anything, cause Ellison et al. (2010) to understate the strength of the relationship between their measures of inter-industry connections and coagglomeration patterns.
One way to check the reasonableness of the geographic coagglomeration relatedness measure is to consider the least and most related industries. At the top of the related list is cotton textile production, followed by cotton textile finishing. Other textile industries, such as woollen, worsted, thread, and miscellaneous weaving, are also among the top 15 most related. This may reflect technological spillovers, labor market pooling, or other forms of inter-industry connections. The third most related industry is paper manufacturing, which may seem odd at first, but an important input for this industry at the time was waste cotton. The sixth most related industry, coal mining, produced the second most important material input for the cotton textile industry. Engine and machine makers, an industry discussed in more detail in Section 4, ranks thirteenth. Toll collector and road construction also rank among the top 15, reflecting the importance of road transport in the cotton districts. Among the fifteen least coagglomerated industries, there are none that one would naturally expect to be related to cotton textiles. Examples include ship transport, sugar refining, cooper, lodging-house keeper, and tobacconist. Overall, it appears that coagglomeration is providing us with a reasonable measure of relatedness between industries.

A coagglomeration measure of relatedness to the wool textile industry, calculated using data from Yorkshire, gives relatedness patterns that are fairly similar to that observed for cotton in Lancashire. The correlation between these two coagglomeration measures is 0.3.

The second measure of relatedness is based on an input-output matrix for intermediate goods. This matrix is based on one constructed by Thomas (1987), and divides the economy into 42 industries. The primary source used by Thomas to construct his input-output matrix was the 1907 Census of Production, Britain’s first industrial census, though he also drew on a wealth of supplementary information. Because this input-output matrix was constructed using data from after the study period, there is some worry that input-output relationships may have changed between the beginning of the study period and the 1907 Census of Production. One way to test for such changes is to compare this input-output matrix to a less detailed matrix constructed by Horrell et al. (1994) for 1841, which divides the economy into 17 categories. Once the categories in these matrices are matched, we find that the correlation between their entries is high (> .96), giving us confidence that our input-output matrix is relevant for the period covered by this study.

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38 A table showing the most and least coagglomerated industries is available in the Appendix.
39 This figure exclude cotton, woollen, and worsted textile manufacturing.
40 Details of the adjustments made to the original Thomas (1987) input-output matrix are available in the Appendix.
4 An Example: Engine & Machine Makers

This section explores the impact of the shock on one related industry, “Engine & Machine Makers” (E&M).\textsuperscript{41} There are two reasons to give the E&M industry special attention. First, a number of scholars have argued that this industry played a central role in the industrial revolution, and in Britain’s economic success throughout the 19th century.\textsuperscript{42} Second, this industry appears to be closely related to the cotton textile industry in Lancashire, and also to the woollen and worsted industries in Yorkshire. Farnie (2004) writes that “Textile engineering became the most important of all the ancillary trades [to cotton textiles]. Its light engineering section supplied spinning machines and looms and a whole succession of related equipment, while its heavy engineering industry supplied steam engines, boilers, and mechanical stokers.” The coagglomeration relatedness measure indicates a high level of relatedness between textile manufacturing and E&M. According to this measure, E&M is the 9th most related industry to cotton textiles in Lancashire (out of the 171 included in the analysis dataset), and the 26th most related to wool textiles in Yorkshire. The intermediate goods input-output matrix does not show significant flows between these industries, since the E&M industry primarily produced capital goods.

Connections between the E&M and cotton textile producers likely took multiple forms. The most obvious connection was direct backward demand linkages from textile producers to the firms supplying their machinery, at least for a subset of E&M firms. Two-way knowledge and technology flows between these industries may have also been important, though evidence of such flows is necessarily sparse. One indication of their importance is the fact that machinery firms often specialized in machinery catered to the needs of producers in their local area. For example, Bolton machine makers dominated the market for machinery to spin fine thread counts, which was mainly produced in the Bolton area,\textsuperscript{43} while Oldham producers were dominant in the machinery for spinning of heavier thread counts, where Oldham producers dominated production. Given the relatively close proximity of these locations, there seem to be few reasons, other than knowledge flows between textile and E&M producers, that explain this specialization pattern. Furthermore, it is well documented that operators in the textile mills were active in “tweaking” their machines, to the point where, for example, “no two pairs of [spinning] mules worked in precisely the same way”\textsuperscript{44}

\textsuperscript{41}Other highly related industries display similar patterns to those described for the E&M industry in this section, including “Worsted Manufacturing”, “Stone Workers”, “Brick Making”, “Dying and Calendering”, “Millwrights”, “Iron Manufacture”, “Hoisery”, “Silk”, and “Flax and Linen”.

\textsuperscript{42}For example, Allen (2009) argues that “the great achievement of the British Industrial Revolution was, in fact, the creation of the first large engineering industry that could mass-produce productivity-raising machinery.”

\textsuperscript{43}See Catling (1986) (ch. 7).

\textsuperscript{44}Lazonick (1990) (p. 96).
seems reasonable to expect that productivity advances made through such tweaking would eventually be incorporated by local machine producers. The textile and engineering industries may have also been linked through labor market connections. Marshall (1920) (p. 226) suggests that textile firms located near E&M firms (or vice-versa) because these industries used complementary sets of labor. Given these connections, we may expect the shock to reduce the growth rate of the E&M industry in locations that were more severely impacted by the cotton shortage.

The pattern of growth of the E&M industry across towns over the study period is explored in Figure 5. The left-hand panel of this figure presents the sum of log employment for towns in Lancashire (high shock intensity) compared to the sum over towns in Yorkshire (low shock intensity). The right-hand panel presents the sum of log employment in towns, where the towns have been grouped based on the share of their employment in cotton textiles in 1851, our instrument for the intensity of the shock. These figures suggest that the shock led to a slowdown in the growth of the E&M industries in locations in which cotton textiles were initially more important, which tended to be the locations that were more severely impacted by the shock. While the increase in log employment was similar in towns with high and low cotton textile employment shares prior to 1861, there was divergence in 1871-1891, with the towns in which cotton textiles were less important gaining a relative advantage in the E&M industry.

Given the available data, it is not possible to pinpoint which types of inter-industry connections are driving the observed effects. However, given that we observe effects which persist several decades after the end of the cotton shortage and the recovery of the cotton textile industry, it is clear that these effects cannot be driven by contemporaneous demand linkages alone. Rather, the appearance of the persistent divergence following the shock suggests that the temporary recession in cotton textile production was transmitted through inter-industry connections and generated long-lasting impacts on the relative productivity

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45 Textile production employed many women and children, while E&M firms employed almost exclusively adult males. Marshall (1920) argued that by co-locating, these firms could pay lower wages and still achieve similar total household incomes levels. Note that this is the opposite of how most economists think of the labor market pooling effect today, which involves benefits to firms employing similar labor forces through co-locating. Marshall acknowledged both of these potential benefits, but less attention has been paid to the benefits of co-location for industries employing different labor forces.

46 Graphs showing the sum of log employment are shown rather than those showing the log of the sum of employment across towns because the former reduces the influence of outlier towns in the graph and also because this corresponds more directly to the econometric methodology. The main outlier is Oldham which was the home of the most dominant engineering firm over the period, Platt Bros. of Oldham, which does not appear to have suffered as much from the shock, perhaps due to the benefits of economies of scale or market power.

47 The groups are: high – Blackburn, Bolton, and Preston; medium – Manchester, Oldham, and Stockport; low – Bradford, Halifax, Huddersfield, Leeds, Sheffield.
of E&M firms in more severely affected locations. In the next section, we present a model describing how such long-term effects can be generated through one type of inter-industry connections: learning-by-doing spillovers.

Figure 5: E&M Industry employment by location

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5 Model

This section presents stylized dynamic Ricardian trade model that describes how a shock can be transmitted across related industries and affect outcomes during and after the shock period. Industries are linked through learning-by-doing spillovers and is closely related to work by Young (1991). There is also a larger related set of literature, including work by Grossman & Helpman (1990), Rivera-Batiz & Romer (1991), Matsuyama (1992), and Feenstra (1996), that considers spillovers using a more limited set of industries and spillover patterns. While learning-by-doing technology spillovers are only one of the set of potential types of inter-industry connections, we have chosen to focus on them because this approach allows a simple representation of inter-industry connections. This is, perhaps, why previous studies in this literature have chosen this approach as well.

The model economy is composed of two locations, called home (H) and foreign (F), and indexed by \( l \in \{H, F\} \). To relate the model to the empirical setting, we can think of home as representing a town in Lancashire, while foreign corresponds to a town in Yorkshire. These locations produce output, trade, and consume. The labor force in each location, \( L_l \), is equal to one. Trade is costless, implying that prices will equalize across locations.

The model is dynamic, but it can be solved iteratively as a series of separate one-period steps, with technology taken as given in any period. The periods are then linked through
technological spillovers, which, being external to firms, do not affect the equilibrium in a particular period. Therefore, we solve a one-period version of the model first and then describe how outcomes from one period determine technology levels in the next. Time subscripts are suppressed until the dynamic elements of the model are introduced.

There are two sectors in the economy, a differentiated good sector, and a homogeneous good sector. The homogeneous good is numeraire, so $p_G = 1$. Individuals’ utility over these sectors is given below, where $D$ is an index of differentiated good consumption, $G$ is consumption of the homogeneous good, and $\mu \in (0, 1)$.

$$U = D^\mu G^{1-\mu}$$

Within the differentiated goods sector, there are a fixed number $N$ goods, indexed by $i \in \{1, ..., N\}$, which also correspond to industries. Individuals’ utility is such that the index of differentiated goods consumption takes a Cobb-Douglas form, where $d_i$ is the quality of consumption of good $i$, $\gamma_i \in (0, 1)$, and $\sum_{i=1}^N \gamma_i = 1$.

$$D = \prod_{i=1}^N d_i^{\gamma_i}$$

Within each industry, home and foreign each produce one variety, so there are $2N$ total varieties of differentiated goods. Preferences over these varieties take a CES form, where $x_{il}$ is consumption of the variety of good $i$ produced in location $l$, and $\rho \in (0, 1)$. The corresponding price index for each differentiated good sector is given by $p_i$, where $q_{iH}$ denotes the price of the variety of good $i$ produced in location $H$, and $\sigma = 1/(1 - \rho) \in (1, +\infty)$.

$$d_i = (x_{iH}^\rho + x_{iF}^\rho)^{\frac{1}{\rho}} \quad p_i = \left(q_{iH}^{1-\sigma} + q_{iF}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

Thus, the economy has three levels of product specificity: the sector level, the goods level, and the variety level. This utility setup may seem over-complicated at first glance, yet it provides some advantages that will help simplify our analysis. First, this framework will allow firms in both locations to produce positive quantities and compete in each industry (though with different varieties), even with perfect competition between firms. Second, the Cobb-Douglas formulation means that shocks to one industry will not impact other industries through general price index effects. This is an important simplification that will allow us to focus only on inter-industry impacts through technology spillovers. Letting $E$ represent total expenditures in the economy, it can be shown that expenditures in each
differentiated goods industries \((E_i)\), and for the homogeneous good \((E_G)\), respectively, are \(E_i = \mu \gamma_i E\) and \(E_G = (1 - \mu)E\).

Next, consider the production side of the economy. The homogeneous good sector is composed of many perfectly competitive firms that produce output using labor only, with the production function \(G = L_G\). If a location produces the homogeneous good, then the wage in that location is \(w_l = p_G = 1\). Production in a differentiated goods industry \(i\) in location \(l\) depends on technology \(A_{il}\) and labor \(L_{il}\). Within each differentiated good industry and location there are many perfectly competitive firms, denoted with the subscript \(f\). Thus, the production function is \(x_{ilf} = A_{il}L_{ilf}\). Firms can freely copy new technologies from one another, so all firms in the same industry and location share the same technology level. However, this information does not flow across locations, so technology in home may differ from that in foreign in the same industry.\(^48\) Given these production functions, perfect competition implies the following price levels for each differentiated good variety.

\[
q_{il} = \frac{w_l}{A_{il}} \quad (1)
\]

The differentiated goods production function, price, and demand equations, can be used to derive output and employment for each industry and variety in the differentiated goods sector, even though output for any particular firm in an industry is indeterminate.

\[
x_{il} = E_i p_i^{\sigma-1} q_{il}^{-\sigma} \quad (2)
\]

\[
L_{il} = E_i p_i^{\sigma-1} q_{il}^{-\sigma} A_{il}^{-1} \quad (3)
\]

Using the price levels for a variety from Equation 1, it is possible to express the price index for each good, and for all goods, in terms of wages, technology, and exogenous parameters only. This in turn allows us to express output and employment in terms of only wages, technology, and exogenous parameters, using Equations 2 and 3.

### 5.1 Solving within a period

Solving for outcomes within a particular period, taking technology as given, involves assuming perfect competition and labor market clearing. The assumption of perfect competition

\(^{48}\)This is consistent with results indicating that spillovers are sharply attenuated with distance. See, e.g., Rosenthal & Strange (2001), Bottazzi & Peri (2003), and Arzaghi & Henderson (2008). Feenstra (1996) shows the importance of this assumption and provides a review of some related empirical literature.
has already been used to derive the price equations above. Labor market clearing requires that the sum of all of the individual labor demands for a location equal the total labor force in that location, i.e., such that \( L = L_G + \sum_{i=1}^{N} L_{il} \). Given Equations 1 and 3, we can write employment in the differentiated goods industry as a function of only wages and expenditures. Expenditures can also be written as a function of wages since, with all income being spent in any given period, it must be the case that \( E = L(w_H + w_F) \). Thus, finding the equilibrium in a particular period amounts to finding the wages that clear the labor market.

In order to simplify the problem, we make the common assumption that the homogeneous good sector is sufficiently large that each location produces at least some homogeneous goods, i.e., let \( 1 - \mu > 1/2 \).\(^{49}\) Under these circumstances \( w_H = w_F = 1 \). This is an important simplification for our analysis, since it will rule out shocks to one industry affecting other industries through wages. While this will aid our theoretical analysis, we will need to be careful to control for potential impacts through wages in the empirical exercise.

Plugging these wages into Equation 1 we obtain prices for each variety and good. We can then calculate employment and output in each differentiated goods industry. Once employment in all differentiated goods industries is calculated, the remainder must be employed in producing the homogeneous good. Before moving on, it is useful to establish one additional fact, which is derived by dividing Equation 3 for home by the same expression for foreign, to obtain Equation 4. This expression shows that, in a particular industry, the location with the better relative technology will have higher employment.

\[
\frac{L_{iH}}{L_{iF}} = \left( \frac{A_{iH}}{A_{iF}} \right)^{\sigma-1} \tag{4}
\]

### 5.2 Linking multiple periods

The model becomes dynamic when outcomes in one period are linked to technology levels in the next. Technological improvements occur as a result of learning-by-doing, as in Arrow (1962) and Lucas (1988). Technological advances occur only in the differentiated good sector; the homogeneous good sector produces no spillovers. The amount of technological advance in an industry depends on the amount of learning generated in the previous period that the industry benefits from. An industry can benefit from both learning generated within the industry (within-industry spillovers) as well as from learning spillovers from related industries (inter-industry spillovers). The amount of learning generated in industry

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\(^{49}\)This approach has been used in existing papers including Krugman & Venables (1995) and Fujita et al. (1999) (ch. 14).
j that industry i benefits from depends on the parameter $\tau_{ij}$, as shown in Equation 5. Thus, there is an $n \times n$ matrix of $\tau_{ij}$ parameters that represent the extent to which learning generated by employment in industry j benefits industry i. The only restriction on these parameters is that $\tau_{ij} \geq 0$ for all i and j.\(^{50}\) Note that in this expression spillovers depend on $L_{jlt} + 1$ rather than simply $L_{jlt}$. This ensures that spillovers from industry j will be zero when $L_{jlt} = 0$ and positive whenever $L_{jlt} > 0$ and $\tau_{ij} > 0$.

\[
\ln(A_{ilt+1}) - \ln(A_{ilt}) = S_{ilt} = \sum_{j=1}^{N} \tau_{ij} \ln(L_{jlt} + 1) \tag{5}
\]

This expression gives the technology level in any period, given outcomes in the previous period. Thus, given a set of initial technology levels, the model can now be solved for all future periods.

### 5.3 A cost shock

The economic shock is introduced into the model as an additional cost $\phi > 0$ that must be paid for production in one differentiated good industry, denoted $i = C$ (for Cotton) for one period, hereafter labeled period s.\(^{51}\) The price for the variety of good C from location l in period s is as follows.

\[
q_{Cls} = \frac{w_{ls}}{A_{Cls}} + \phi \tag{6}
\]

Observation 1 describes the effects of the shock in the shock period, where we presume that industry C has better technology in home than in foreign at the beginning of the shock period.

\(^{50}\)It may be surprising at first that we do not assume that within-industry spillovers are larger than cross-industry spillovers, but there are reasons to think that cross-industry spillovers may be larger. For example, firms may have more incentive to hide knowledge from competitors in their industry but to collaborate with firms in other industries. See Kugler (2006) for more on this topic.

\(^{51}\)This reduced-form approach can be motivated by a model that explicitly incorporates intermediate goods in production, as shown in the Appendix.
**Obs. 1** A cost shock affecting industry C in period s, with $A_{CHs} > A_{CFs}$, will have the following effects.

1. Employment in industry C, in the shock period, will fall in the location with better technology in industry C (home). The log difference $\ln(L_{CHs}) - \ln(L_{CFs})$ will also fall.
   
   $$\frac{dL_{CHs}}{d\phi} < 0 \quad \text{and} \quad \frac{d(\ln(L_{CHs}) - \ln(L_{CFs}))}{d\phi} < 0 \quad \text{when} \quad A_{CH} > A_{CF}$$

2. Employment in all other industries will be unaffected by the shock in period s,
   
   $$\frac{dL_{ils}}{d\phi} = 0$$

The intuition behind part (1) is that, because home is initially more productive in industry C, $\phi$ will be a larger share of the production cost in home than in foreign. In part (2), other industries are not impacted because we have ruled out wage and price index effects between industries, as can be seen in Equation 3, in order to focus on effects occurring through non-pecuniary channels. A formal proof is available in the Appendix.

### 5.4 Impact of the shock on related industries

Using Equations 3 and the expression for $S_{ilt}$ given in Equation 5, we can make some observations on the effect of the shock on related industries in future periods. First, consider the impact of a reduction in employment in the industry receiving the negative cost shock on related industries. The result, stated below, follow directly from Equations 3 and 5.

**Obs. 2** If industry $i$ benefits from spillovers from industry C ($\tau_{iC} > 0$), then a decrease in $L_{Cils}$, will cause a decrease in $S_{ils}$, $A_{ils+1}$, and $L_{ils+1}$. The greater is $\tau_{iC}$, the larger will be the effect.

Given that employment in industry C falls, at least in H, where that industry is most productive, we know that related industries will suffer a loss of spillovers in H. Next, we are interested in how the magnitude of these effects in H compare with those in F, where the impact of the shock, in terms of the total employment lost in industry C, is less severe.
Obs. 3 The loss of spillovers in industries related to industry C in the shock period s will be larger in the location in which industry C is initially more productive. I.e., for some industry i with $\tau^{iC} > 0$,

$$\frac{dS_{iHs}}{d\phi} > \frac{dS_{iFs}}{d\phi} \text{ when } A_{CHs} > A_{CFs}$$

The intuition here is that the loss of spillovers in related industries will be larger in the location in which the loss of employment in industry C is greater. A formal proof is available in the Appendix. Naturally, the differential impact on the level of spillovers in period s will lead to differential impacts on the level of technology and employment in period s+1. The results above describe the impact of the shock on technology and employment in related industries in period s+1. We can also speculate about the impacts in periods beyond s+1, though here the effects will become more complicated.

Obs. 4 If industry i benefits from spillovers from industry C, then a shock to industry C can affect employment in industry i in future periods through three channels: (1) through reducing $L_{ilt}$, which, in the presence of within-industry spillovers, reduces the spillovers available to industry i and therefore reduces $A_{ilt+1}$ and $L_{ilt+1}$; (2) through long-term effects on employment in industry C which affect the spillovers from industry C to industry i in future periods; (3) through affecting employment in other industries, which, if these industries are also related to i, affects the spillovers available to industry i in the future;

These three channels can be seen more clearly by decomposing the spillovers term. In the equation below, the first term on the right-hand side represents channel (1), the second term represents channel (2), and the third term represents channel (3).

$$S_{ilt} = \tau^{ii}ln(L_{ilt} + 1) + \tau^{iC}ln(L_{Cilt} + 1) + \sum_{j \neq i,C}^{N} \tau^{ij}ln(L_{jilt} + 1)$$

The nature of these long-run impacts on related industry i are not clear, due to the complex effects that the shock can have on employment in other related industries, which can impact future spillover levels in unexpected ways. However, it is clear that, in the presence of within-industry spillovers, the impact of the shock through channels (1) and (2) will be negative for more related industries in more severely impacted locations. The impact through channel (3) is indeterminate, but if industries related to industry i are also related to industry C, as we would expect if there are clusters of related industries, then the impact through channel (3) is also likely to be negative for more related industries in more severely impacted locations.
Of these three channels, channel (3) is the most elusive, but it may well be the most important. Previous studies looking at the impacts of spillovers through input-output linkages due to FDI, such as Aitken & Harrison (1999), have found little evidence of spillovers between firms within the same industry. On the other hand, studies such as Javorcik (2004), Kugler (2006), and Amiti & Cameron (2007) have found evidence of spillovers between firms in different industries. Kugler (2006) argues that this makes sense, because firms are likely to hide information from their competitors while cooperating with firms that they do not compete with, such as their suppliers and customers.

6 Econometric analysis

The model suggests that the shock should have a negative impact on those industries related to the cotton textile industry and that this impact should be larger in those locations which were more severely impacted by the shock, which also happen to be the locations which were initially more productive in the cotton textile industry. This section tests this prediction. The empirical strategy involves a fixed effect regression approach where the panel has two cross sectional dimensions (towns and industries). Thus, we are comparing across time (pre-vs. post-shock), industries (more vs. less related to cotton textiles), and locations (more vs. less severely impacted by the shock).

The first step is to derive a usable empirical specification from the model. The basis for our empirical specification is Equation 3, which describes employment in industry i and location l as a function of expenditures on goods in industry i, the price index for goods in industry i, and the productivity of location l in producing its variety of good i. Taking logs and substituting out \( q_{ilt} \) using Equation 1 and \( A_{ilt} \) using the technology growth expression from Equation 5, we obtain the following.

\[
\ln(L_{ilt}) = \ln(\mu \gamma_i E) + (\sigma - 1) \ln(p_{it}) + (\sigma - 1) \ln(A_{ilt-1}) + (\sigma - 1) S_{ilt-1}
\]

This expression will motivate the empirical exercises. The key to the empirical strategy will be using the shock, interacted with industry relatedness, as a proxy for the spillovers term, while controlling for factors that vary at the industry-period, location-period, and industry-location level.

Our first test of the model is based on the specification given in Equation 7 below, where \( R_i \) represents industry i's relatedness to the cotton textile industry, \( V_l \) represents the intensity of the shock in town l, \( Post_t \) indicates the post-shock period. We control for factors that vary at the industry-year level, such as \( p_{it} \) by including industry-year dummy
variables, \( \theta_{it} \). Factors varying at the location-period level, though not present in the stylized model above, must also be considered. These are controlled for by including location-year dummy variables, \( \psi_{lt} \). Finally, we allow for variation at the industry-location level by including industry-location fixed effects, \( \xi_{il} \). Note that because we are estimating a fully saturated fixed-effect model, lower-level interaction terms are not included, since they would be perfectly correlated with the fixed effects.

\[
\ln(L_{ilt}) = \beta_0 + \beta_1 (R_i \times V_l \times Post_t) + \theta_{it} + \psi_{lt} + \xi_{il} + \epsilon_{ilt} \tag{7}
\]

While Equation 7 will be useful for studying whether the shock had an impact on the level of employment in related industries, we also want to consider the possibility that the growth rate of related industries may have also been impacted. A simple way to look for this is using Equation 8 below, where \( T_t \) is a time-trend variable for the post-shock period \( (T_{1851} = 0, T_{1861} = 0, T_{1871} = 1, T_{1881} = 2, T_{1891} = 3) \).

\[
\ln(L_{ilt}) = \beta_0 + \beta_1 (R_i \times V_l \times T_t) + \theta_{it} + \psi_{lt} + \xi_{il} + \epsilon_{ilt} \tag{8}
\]

The main coefficient of interest will be \( \beta_1 \). A negative \( \beta_1 \) coefficient estimate would suggest that the shock had a negative impact on more related industries in more severely impacted towns, supporting the predictions of the model. Identification relies on the assumption that there are no omitted variables that change between the pre and post-shock time periods, affect related industries more than unrelated industries, and are stronger in those towns more severely hit by the shock. One concern that we may have with these identification assumptions is that the severity of the shock, as measured by the number of able-bodied workers seeking relief from Poor Law boards in each town, may reflect changes in the economic conditions in these towns occurring at the same time as the shock which are not driven by the shock. To strengthen our identification strategy against this concern, for each specification we will calculate results in which the employment share of cotton textile production in 1851 in each location is used as an IV for the severity of the shock (interacted with the other terms). We would not expect that having a larger share of cotton textile employment in 1851 would cause a change in the performance of related industries after 1861, but not before, other than through the effects of the shock. The results in Table 3 suggest that this will be a very strong instrument.

Because we are interested in spillovers across industries, we exclude cotton textile production and other cotton-based industries from the analysis.\(^{52}\) These industries differ fundamentally from all others in that they were directly impacted by the shock regardless of

\(^{52}\)The excluded industries are “Cotton manufacturing”, “Fustian manufacturing” (a cotton-linen mix fabric), “Cotton textile printing and dying”, “Other workers and dealers in cotton”, “Cotton thread manu-
their location. In order to better handle serial correlation issues, standard errors are clustered at the industry-location level.\footnote{Alternatively, we may have chosen to cluster at the industry or the town level. Results, available in the Appendix, suggest that our results are robust to these alternatives.} This allows for standard errors to be correlated over time within an industry-location, in order to deal with potential serial correlation issues.\footnote{Bertrand et al. (2004) show that serial correlation issues can be important in differences-in-differences estimation, though the structure of the data used in this study, with its large cross section and relatively short time dimension, makes serial correlation less of a worry. See also Angrist & Pischke (2009). Another potential issue, pointed out by Donald & Lang (2007), is that t-statistics may suffer when the number of clustered groups is small. However, because this study uses data from a relatively large number of clustered groups (171), this should not be a major concern.} In order to make the results easier to interpret, the continuous variables, the shock intensity measure and relatedness measures, are standardized to have a mean of zero and standard deviation of one. Summary statistics for the data used in the analysis are available in the Appendix.

Baseline regression results for Equations 7 are given in Table 4. These results are calculated using a standard fixed-effects approach at the industry-location level, for the 1,543 unique industry-locations in the data, while including industry-year and location-year dummy variables. Columns (1) and (2) calculate results using the coagglomeration and input-output relatedness measures, respectively, while both measures are included in column (3). Column (4) presents “reduced form” results, where the share of cotton textile employment to total employment in each location is used in place of the shock severity measure based on number of relief seekers. Columns (5)-(7) present IV results in which the share of cotton textile employment to total employment in each location is used as an IV for the severity of the shock in each location in a Two-Stage Least Squares regression.

The results in Table 4 suggest that log employment was negatively impacted by the shock in more related industries, based on the coagglomeration measure, in more severely affected towns. No similar negative impacts appear for those industries linked to cotton textiles through input-output connections, and the coagglomeration measure results continue to be significant when the input-output measure is included. This suggests that the negative employment impacts are driven by some channel other than direct input output linkages. In terms of magnitude, these results suggest that in a location that is one standard deviation above the mean in terms of shock severity, an industry that is one standard deviation above the mean in relatedness would suffer a relative reduction in employment of 4.5-7%. Put another way, the predicted impact on an industry with a relatedness measure equal to that of the Engine & Machine Makers (1.27 s.d.), in the most severely impacted town Preston (1.77 s.d.) is a relative employment reduction of 10-16% in the post-shock period.
Table 4: Fixed effect regression results for Eq. 7

<table>
<thead>
<tr>
<th></th>
<th>Coag. only</th>
<th>IO only</th>
<th>Both</th>
<th>Reduced form</th>
<th>IV Coag</th>
<th>IV IO</th>
<th>IV Both</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coag. * Shk * Post</td>
<td>-0.0472***</td>
<td>-0.0486***</td>
<td>-0.0600***</td>
<td>-0.0797***</td>
<td>-0.0806***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0183)</td>
<td>(0.0182)</td>
<td>(0.0189)</td>
<td>(0.0246)</td>
<td>(0.0244)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IO * Shk * Post</td>
<td>0.0480</td>
<td>0.0536*</td>
<td>0.0238</td>
<td>0.0217</td>
<td>0.0320</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0305)</td>
<td>(0.0305)</td>
<td>(0.0351)</td>
<td>(0.0452)</td>
<td>(0.0450)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Ind-loc FEs      | Yes        | Yes      | Yes   | Yes          | Yes     | Yes   | Yes     |
Ind-year dummies | Yes        | Yes      | Yes   | Yes          | Yes     | Yes   | Yes     |
Loc-year dummies | Yes        | Yes      | Yes   | Yes          | Yes     | Yes   | Yes     |
Observations     | 7,715      | 7,715    | 7,715 | 7,715        | 7,715   | 7,715 | 7,715   |

Robust standard errors in parentheses  *** p<0.01, ** p<0.05, * p<0.1

Table 5, which has the same format as Table 7, shows results corresponding to Equation 8. This allows us to study whether we still observe the same results when we allow for simple linear growth trend in the impact of the shock on related industries in more severely impacted locations. The main variable of interest is then $Coag.\times ShockInt.\times TT$. The coefficients on this term continue to be negative and strongly statistically significant, providing some evidence that the shock may have impacted the growth rate in log employment, in addition to the level.

An alternative approach to the more standard fixed effects is to use first-differencing. First differencing will be efficient when error terms follow a random walk, which seems likely in our setting. First difference results are calculated using the following two specifications. In Equation 9, $T_{1871}$ is an indicator variable for the year 1871, the first post shock year. Thus, this expression allows us to test for impact on the level of employment in related industries. In Equation 10, $Post_1$ is an indicator for the post shock period. This expression allows us to test for persistent impacts on the change in log employment in related industries.

$$\Delta \ln(L_{ilt}) = \beta_0 + \beta_1(R_i \times V_i \times T_{1871}) + \theta_{it} + \psi_{lt} + \Delta \epsilon_{ilt}$$  \hspace{1cm} (9)

$$\Delta \ln(L_{ilt}) = \beta_0 + \beta_1(R_i \times V_i \times Post_1) + \theta_{it} + \psi_{lt} + \Delta \epsilon_{ilt}$$  \hspace{1cm} (10)

Results for OLS regressions based on Equation 9 are presented in Table 6. These results are qualitatively similar to those obtained using the fixed effects, but the magnitudes are somewhat smaller and the coefficients are not statistically significant. Results for OLS
regressions based on Equation 10 are presented in Table 7. Here we observe fairly strong evidence that the shock had a negative impact on the growth in log employment in more related industries and more severely impacted locations in the post-shock period. It appears that both the fixed effects and first differences approaches indicate that the shock had persistent impacts.

It is also interesting to consider the impact of the shock year-by-year. This can be done by allowing by estimating separate coefficients on the interaction term for each post-shock year, rather than using the post-shock flag, which requires that the coefficient be the same for all years. Table 8 presents year-by-year results. These results indicate that the shock had a negative impact in all post-shock periods on related industries, based on
Table 7: First-difference regression results for Eq. 10

<table>
<thead>
<tr>
<th>Coag. * Shk * Post</th>
<th>-0.0230**</th>
<th>-0.0235**</th>
<th>-0.0252***</th>
<th>-0.0336***</th>
<th>-0.0339***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.00959)</td>
<td>(0.00958)</td>
<td>(0.00941)</td>
<td>(0.0119)</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>IO * Shk * Post</td>
<td>0.0171</td>
<td>0.0199</td>
<td>0.00779</td>
<td>0.00607</td>
<td>0.0105</td>
</tr>
<tr>
<td></td>
<td>(0.0144)</td>
<td>(0.0142)</td>
<td>(0.0164)</td>
<td>(0.0210)</td>
<td>(0.0207)</td>
</tr>
<tr>
<td>Ind-year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Loc-year dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>6,172</td>
<td>6,172</td>
<td>6,172</td>
<td>6,172</td>
<td>6,172</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

the coagglomeration measure, and that the impact was growing over time. As before, no consistent impacts are observed in those industries related through input-output linkages, though it does appear that input-output related industries may have experienced some positive impacts in 1871.

Table 8: Year-by-year regression results

<table>
<thead>
<tr>
<th>Coag. * Shk * 1871</th>
<th>-0.0346**</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.0151)</td>
</tr>
<tr>
<td>Coag. * Shk * 1881</td>
<td>-0.0288</td>
</tr>
<tr>
<td></td>
<td>(0.0207)</td>
</tr>
<tr>
<td>Coag. * Shk * 1891</td>
<td>-0.0782***</td>
</tr>
<tr>
<td></td>
<td>(0.0269)</td>
</tr>
<tr>
<td>IO * Shk * 1871</td>
<td>0.0549**</td>
</tr>
<tr>
<td></td>
<td>(0.0262)</td>
</tr>
<tr>
<td>IO * Shk * 1881</td>
<td>0.0434</td>
</tr>
<tr>
<td></td>
<td>(0.0427)</td>
</tr>
<tr>
<td>IO * Shk * 1891</td>
<td>0.0457</td>
</tr>
<tr>
<td></td>
<td>(0.0401)</td>
</tr>
<tr>
<td>Ind-loc FEs</td>
<td>Yes</td>
</tr>
<tr>
<td>Ind-year dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Loc-year dummies</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>7,715</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
We have shown that our results tend to be robust to changes in the estimation specification. We can also check their robustness to changes to the data used to estimate the results. Table 9 presents results that assess the robustness of our findings to several changes in the data used in the estimation. Columns (1) and (2) present results calculated when data from Liverpool is included. Column (1) presents fixed effects results including both relatedness measures, and column (2) presents IV results. Recall that Liverpool was excluded because industries other than cotton textiles were directly impacted by the civil war there. Including Liverpool does not appear to alter our results.

Another potential issue arises from the fact that the set of towns used to obtain our results may also influence the coagglomeration measure. To see why this might cause an issue, suppose that the coagglomeration measure simply reflects a random chance that an industry ends up coagglomerated with cotton textiles, rather than underlying connections between these industries. Furthermore, suppose that when cotton textiles is shocked in a location all industries in that location suffer, with the industries more agglomerated in the location suffering more. This scenario may cause errant results if the coagglomeration measure is driven by the towns used in our analysis. This is unlikely because we have calculated coagglomeration using district-level, rather than town-level data, which covers many areas other than the towns used in the analysis. However, if one is still worried that the towns used are driving the coagglomeration measure, then results can be recalculated using a coagglomeration measure calculated using only districts that do not include towns used in the subsequent analysis. Results using this alternative coagglomeration measure are presented columns (3) and (4) of Table 9.

Columns (5) and (6) of Table 9 present results when all wool-related industries have been dropped from the analysis. While these are an important class of industries which are closely related to the cotton textile industry, we may be worried that the fact that they are initially much larger in Yorkshire towns could lead them to grow faster there, in the presence of economies of scale or within-industry spillovers. While dropping these industries does reduce the size of the estimated impact, it does not alter the basic message. Finally, columns (7) and (8) include results in which all industries sharing intermediate good input-output connections with the cotton textile industry have been excluded from the analysis. This appears to strengthen our results, providing further evidence that the observed impacts were not driven by intermediate goods input-output connections.

Three innovations offered by this study, vis a vis existing studies, is the use of geographically disaggregated data, the use of more detailed industry-level data, and accounting for the pattern of inter-industry connections. Given that our results differ from previous studies which find that temporary shocks have few long-term impacts, such as Davis & Weinstein (2008), it is interesting to look at which of these innovations appears to be driving our
Table 9: Some robustness checks

<table>
<thead>
<tr>
<th></th>
<th>With Liverpool</th>
<th>Alt. Coag. Measure</th>
<th>Without Wool</th>
<th>No IO Inds.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Reg.</td>
<td>IV</td>
<td>Reg.</td>
<td>IV</td>
</tr>
<tr>
<td>Coag<em>Shk</em>Pst</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>-0.0516***</td>
<td>-0.0819***</td>
<td>-0.0464**</td>
<td>-0.0779***</td>
</tr>
<tr>
<td></td>
<td>(0.0173)</td>
<td>(0.0227)</td>
<td>(0.0194)</td>
<td>(0.0253)</td>
</tr>
<tr>
<td>IO<em>Shk</em>Pst</td>
<td>0.0401</td>
<td>0.0132</td>
<td>0.0501*</td>
<td>0.0265</td>
</tr>
<tr>
<td></td>
<td>(0.0284)</td>
<td>(0.0413)</td>
<td>(0.0304)</td>
<td>(0.0451)</td>
</tr>
<tr>
<td>Ind-loc FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Ind-year dum.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Loc-year dum.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Obs</td>
<td>8,535</td>
<td>8,535</td>
<td>7,715</td>
<td>7,715</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

results. To analyze the impact of using geographically disaggregated data, we can apply our estimation strategy at a less disaggregated level, by comparing outcomes in the county of Lancashire as a whole to outcomes in Yorkshire. This analysis follows that shown in Equation 7 except that a flag for Lancashire is used in place of the shock severity measure. Results calculated using these county-level data are presented in Table 10, columns (1)-(2). While these results have the same sign as those found with the full data set, they are not statistically significant. Thus, had we used less geographically disaggregated data we would not have found strong evidence that the shock impacted related industries.

In order to assess the importance of using data that are more disaggregated at the industry level, we can repeat our analysis across more aggregated industry sectors. For comparability, we use the eight broad industrial sectors used in Davis & Weinstein (2008). These sectors are Machinery, Metals, Chemicals, Textiles and Apparel, Processed Food, Printing and Publishing, Lumber and Wood, and Ceramics. Industries not fitting into one of these categories are dropped. The relatedness between the remaining categories and the Textile and Apparel category are then calculated using the geographic coagglomeration measure. Then the Textiles and Apparel sector is excluded and results are calculated using the approach in Equation 7. Results, shown in Table 10, columns (3)-(6), suggest that had we used data aggregated to these eight industrial sectors we would have found only weak evidence that the shock affected the level of employment in related industries.

---

55 As before, Lancashire includes neighboring Cheshire county while only the West Riding is included in Yorkshire.
### Table 10: Regression results using less disaggregated data

<table>
<thead>
<tr>
<th></th>
<th>County-level regs.</th>
<th>Regs with DW2008 sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Coag. * Lanc * Post</td>
<td>-0.0203 (0.0376)</td>
<td>-0.0569 (0.0400)</td>
</tr>
<tr>
<td>IO * Lanc * Post</td>
<td>0.0127 (0.0759)</td>
<td></td>
</tr>
<tr>
<td>Coag. * Lanc * TT</td>
<td>-0.00877 (0.00172)</td>
<td>-0.0318* (0.0182)</td>
</tr>
<tr>
<td>IO * Lanc * TT</td>
<td>0.00295 (0.0349)</td>
<td></td>
</tr>
<tr>
<td>Industry-location FEs</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry-year dum.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Location-year dum.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,710</td>
<td>1,710</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

Finally, we can calculate results while ignoring industry connections. This is done using the specifications in Equations 11 and 12, which estimate the impact of the shock based only on the severity in each location. For these specification, it makes more sense to cluster errors at the location level, since the shock to each location is assumed to impact all of the industries in that location.

\[
\ln(L_{ilt}) = \beta_0 + \beta_1(V_{i} \ast Post_t) + \theta_{it} + \xi_{ilt} + \epsilon_{ilt}
\]  
\[
\ln(L_{ilt}) = \beta_0 + \beta_1(V_{i} \ast T_t) + \theta_{it} + \xi_{ilt} + \epsilon_{ilt}
\]  

Regression results are shown in Table 11, where the top half of results correspond to Equation 11 and the bottom half show results from separate regressions using Equation 12. Columns (1)-(2) present baseline and IV results, respectively, ignoring inter-industry connections. As before, we observe a negative effect on industries in more severely impacted towns, but these results are not statistically significant. Thus, had we ignored the pattern of inter-industry connections, we would not have found strong evidence that the shock had a long-term impact. To learn more, we run separate regression for only those industries with positive coagglomeration relatedness measures, in columns (3)-(4) and only those with negative coagglomeration relatedness measures, in columns (5)-(6). We observe that the coefficients measuring the impact of the shock are much larger (more negative) for the more related industries than for the less related industries, though the results for the more related
Table 11: Results calculated ignoring inter-industry connections

<table>
<thead>
<tr>
<th></th>
<th>All ind.</th>
<th>Positive coag.</th>
<th>Negative coag.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline IV</td>
<td>Baseline IV</td>
<td>Baseline IV</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Shock Int. * Post</td>
<td>-0.101* (0.0515)</td>
<td>-0.162 (0.0924)</td>
<td>-0.0879* (0.0438)</td>
</tr>
<tr>
<td></td>
<td>-0.105 (0.0655)</td>
<td>-0.211 (0.140)</td>
<td>-0.0819 (0.0558)</td>
</tr>
<tr>
<td>Shock Int. * TT</td>
<td>-0.0334 (0.0251)</td>
<td>-0.0592 (0.0447)</td>
<td>-0.0279 (0.0214)</td>
</tr>
<tr>
<td></td>
<td>-0.0310 (0.0303)</td>
<td>-0.0776 (0.0671)</td>
<td>-0.0210 (0.0247)</td>
</tr>
<tr>
<td>Industry-location FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry-year dum.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>7,715</td>
<td>1,385</td>
<td>6,330</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses  *** p<0.01, ** p<0.05, * p<0.1

industries are still not statistically significant, likely due to the much reduced sample size. In sum, these results indicate the importance of accounting for the pattern of inter-industry connections in obtaining our results.

Together, the results shown in Tables 10 and 11 indicate that obtaining our results depended both on the use of detailed data, both in terms of industries and geographic locations, as well as paying attention to the patterns of connections between industries. The combination of these elements may help explain why our results differ from those found in previous studies. We cannot, however, rule out other factors, such as the fact that we consider a shock driven by economic forces while existing studies consider shocks generated by war.

7 Conclusion

This project describes a large, exogenous, industry-specific shock to the 19th century British economy and shows that it affected the distribution of industries across locations up to 25 years after the end of the shock. In particular, it shows that those industries more closely related to the industry which was directly affected, cotton textiles, suffered long-term reductions in employment and employment growth, in those towns which were more severely affected by the shock. This provides causal evidence that inter-industry spillovers can transmit negative shocks with long-term effects. These effects are of significant magnitude and longevity given the transient nature of the shock considered.

These results have implications for two types of policies. First, while this study focuses
on a large negative shock caused by exogenous factors, it seems possible that localized industrial policy interventions may be able to generate similar effects. This may provide some justification for the widespread use of these policies. However, these results also suggest that the effectiveness of such policy interventions depends crucially on the pattern of connections between industries, which are currently not well understood.

These results also have implications for policies that may influence the vulnerability of an economy to economic shocks, because they suggest that even temporary shocks, if large enough, can have long-lasting effects. While this study shows how a temporary shock can reallocate industries within a country, the same forces are also likely to be at work across countries. Thus, policy makers may want to consider the potential effects of volatility when considering policies that increase and economy’s vulnerability to temporary shocks.

While this study tells us that inter-industry connections can transmit economic forces between industries, with long-term implications, we are unable to identify the particular types of connections that are most important, though it does not appear that intermediate good input-output linkages are driving the observed results. More clearly identifying the particular types of industries that drive the effects we observe is an important direction for future research.
References


Poole, J. 2009. *Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility*. Working paper.


Appendix

This appendix provides additional information that may be helpful in understanding and replicating the results presented in the paper. It is divided into four sections. The first section provides some additional background information on the empirical setting. The second section provides additional information on the procedures used to construct the data. The third section presents additional results and proofs related to the theory. The fourth section provides supplementary statistical results.

A Empirical setting appendix

Figure 6 was adapted from Catling (1986) and shows the variation in different production activities across major cotton-textile producing towns considered in this study. This map shows that weaving was concentrated in the northern towns, Preston and Blackburn, spinning was concentrated in the southern towns of Bolton, Oldham, and Stockport, and most finishing was done in Manchester.

Figure 6: Distribution of cotton textile manufacturing stages in Lancashire towns

Adapted from Catling (1986).

Figure 7 presents data describing total British cotton imports, and British cotton imports from the U.S., from 1815-1910. This chart shows that, just prior to the start of the Civil War, the majority of Britain’s cotton supplies were coming from the U.S., but that these imports dropped nearly to zero during most of the 1861-1865 period. While imports from other suppliers increased, they were not able to make up for the drop in U.S. cotton, 40
leading to a sharp drop in overall cotton imports during the Civil War. However, imports quickly rebounded following the end of hostilities.

Figure 7: Total British cotton imports and imports from the U.S. 1815-1910

This paper argues that the shock was primarily industry-specific. Figure 8 provides data supporting this argument. The left-hand panel shows that there was no visible effect on total British imports, or British raw material imports, once raw materials for textiles are excluded. The right-hand panel shows that, once textile exports are excluded, the shock does not appear to have affected British exports of manufactured goods.

Figure 8: British imports and exports 1851-1869

Data from Mitchell (1988).
B Data appendix

B.1 Census data

The census data were taken from the original Census Enumerator Reports for 1851-1891, which are available at the British Library.

Town-level data

Town level data for these years and counties was available only for the towns used in the analysis, plus Liverpool. Salford is treated as part of Manchester, consistent with their very close proximity. Data for males and females were combined in all analysis. The data for 1851-1861 are available divided into workers over 19 and workers under 20, by occupation. In 1871, data by occupation are available only for workers over 19, while in 1881-1891 data are only available for all workers. It is, therefore, necessary to estimate values for 1871 employees under 20, as this was an important fraction of the labor force at this time. This is done by calculating the average ratio of all employees, to employees over 20, in each industry and location, in 1851 and 1861, and then multiplying this value by the number of employees in each industry and location in 1871, to obtain 1871 values that are consistent with the other years.

Matching occupations/industries over time
Industry categories changed over time, so it was necessary to combine multiple industries in order to construct more consistent industry groupings over the study period. Individual categories in the years were combined into industry groups based on (1) the census’ occupation classes and (2) the name of the occupation. For some occupations, it was not possible to form consistent groups over all years, and these occupations are omitted from the analysis. It is still the case that some occupation groups may not be perfectly consistent over time, however, because our identification strategy controls for aggregate industry-year effects, it should be less affected by this source of measurement error. The occupational categories prior to 1851 and after 1891 change significantly, relative to the period that we study, which motivates our choice of study period.

Calculating geographic coagglomeration

The measure of geographic coagglomeration is based on Ellison et al. (2010) and is calculated using data from 71 district within Lancashire. The use of data from only Lancashire here is important. There are two good reasons for taking this approach. First, it is the pattern of relatedness in Lancashire that determines which industries are affected by the shock. Thus far, little is known about the extent to which deep patterns of industry relatedness vary across locations. Using only one location minimizes this concern. Second, there is a danger in calculating coagglomeration measures over too broad an area. To see why, consider some industry \(x\) which is related to both the cotton and wool textile industries and is coagglomerated with cotton textiles in Lancashire and wool textiles in Yorkshire. If the coagglomeration measures is calculated using only Lancashire county, we find that industry \(x\) is coagglomerated with cotton textiles. If data from Yorkshire are added, there will be a sharp reduction in the level of coagglomeration of industry \(x\) with cotton textiles, because there are now concentrations of industry \(x\) in Yorkshire districts with very little cotton textile production (but a lot of wool textile production). To calculate the measure, we suppose that there are \(M\) districts, and let \(s_{mi}\) be the share of industry \(i\)’s employment in some district \(m\). Let \(x_m\) be district \(m\)’s share of workers. Geographic coagglomeration between industries \(i\) and \(j\) is given by \(R_{ij}\), where,

\[
R_{ij} = \frac{\sum_{m=1}^{M} (s_{mi} - x_m)(s_{mj} - x_m)}{1 - \sum_{m=1}^{M} x_m^2}
\]

Table 12 gives the fifteen most and least related industries to the cotton textile industry, according to the coagglomeration measure. Note that, for illustration, this table includes cotton-based industries which are later excluded from the analysis.
Table 12: Most and least coagglomerated industries with cotton textiles

<table>
<thead>
<tr>
<th>Rank</th>
<th>Most coagglomerated</th>
<th>Least coagglomerated</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cotton textile manufacturing</td>
<td>Ship transport</td>
</tr>
<tr>
<td>2</td>
<td>Cotton textile finishing</td>
<td>Sugar refining</td>
</tr>
<tr>
<td>3</td>
<td>Paper manufacturing</td>
<td>Shipbuilding</td>
</tr>
<tr>
<td>4</td>
<td>Hat making</td>
<td>Hemp, sacking, and sailcloth</td>
</tr>
<tr>
<td>5</td>
<td>Worsted and stuff manufacturing</td>
<td>Cooper</td>
</tr>
<tr>
<td>6</td>
<td>Coal mining</td>
<td>Silk mercer</td>
</tr>
<tr>
<td>7</td>
<td>Fuller (wool textile finishing)</td>
<td>Soap maker</td>
</tr>
<tr>
<td>8</td>
<td>Woollen textile manufacturing</td>
<td>Hemp, jute manufacture</td>
</tr>
<tr>
<td>9</td>
<td>Stone worker</td>
<td>Musical instrument maker</td>
</tr>
<tr>
<td>10</td>
<td>Toll collector</td>
<td>Lodging house keeper</td>
</tr>
<tr>
<td>11</td>
<td>Weaver, misc.</td>
<td>Tobacconist</td>
</tr>
<tr>
<td>12</td>
<td>Thread manufacturing</td>
<td>Messenger, porter</td>
</tr>
<tr>
<td>13</td>
<td>Engine and machine maker</td>
<td>Artificial flower maker</td>
</tr>
<tr>
<td>14</td>
<td>Road construction</td>
<td>Timber cutting</td>
</tr>
<tr>
<td>15</td>
<td>Brick making</td>
<td>Watch making</td>
</tr>
</tbody>
</table>

B.2 Input-output matrix

Relatedness between industries based on the input-output matrix can be measured either through upstream, downstream, or both types of connections. Downstream connections from cotton textiles to another industry are measured by the share of that industry’s inputs composed of cotton textile outputs. Similarly, upstream connections between cotton textiles and its supplier industries are measured as the share of the supplier industry’s output sold to the cotton textile industry. These two measures are combined to obtain the input-output connections measure used in the analysis. This matches the approach used in Ellison et al. (2010).

The input-output matrix used in this project is derived from that produced by Thomas (1987), which includes 41 categories. While this matrix is generally suitable for the project at hand, one revision is necessary. Thomas’ matrix combined the cotton and silk textile industries. If we treat silk as if it were the same as cotton, we end up with an unrealistically high measure of the input-output linkages between these two industries. Therefore, it was necessary to separate the silk and cotton industries, creating one additional entry in the input-output matrix. Thomas’ sources and methodology were followed as closely as possible in separating these two industries. The primary information used to create the separate silk entry came from the same source used by Thomas in the original matrix, the 1907 Census of Production.
Relatedness measure distributions

The following four figures describe the distribution of industry relatedness arising from the coagglomeration and input-output relatedness measures. The left-hand panels provide the raw distribution, while the right-hand panels present the distribution where each industry has been weighted by its employment in 1851.

Figure 10: Histograms describing the coagglomeration relatedness measure (171 industries)

Figure 11: Histograms describing the input-output relatedness measure (43 sectors)

Summary statistics for analysis data

The table below presents simple summary statistics for the data used in the primary analysis. Note that the continuous variables have been standardized to have a mean of zero and standard deviation of one.

45
Table 13: Summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln(Emp.)- Town level</td>
<td>6907</td>
<td>3.88</td>
<td>2.03</td>
<td>0</td>
<td>10.48</td>
</tr>
<tr>
<td>Ln(Emp.)- County level</td>
<td>1710</td>
<td>7.08</td>
<td>1.80</td>
<td>0</td>
<td>12.15</td>
</tr>
<tr>
<td>Coag Input-Output</td>
<td>42</td>
<td>0</td>
<td>1.00</td>
<td>-0.35</td>
<td>4.37</td>
</tr>
<tr>
<td>Shock severity</td>
<td>11</td>
<td>0</td>
<td>1.00</td>
<td>-0.86</td>
<td>1.77</td>
</tr>
<tr>
<td>1851 cotton emp. share</td>
<td>11</td>
<td>0</td>
<td>1.01</td>
<td>-0.88</td>
<td>1.29</td>
</tr>
</tbody>
</table>

C Theoretical appendix

This section presents some additional work related to the theory. The first subsection provides a more rigorous proof of equilibrium existence for the theoretical model. Next, we show that the cost shock formulation used in the model can be derived from a micro-founded model. Finally, we present more rigorous proofs supporting the assertions made in Obs. 1.

C.1 Derivation of the shock period cotton textile price equation

This subsection describes how the reduced form approach used to introduce the cost shock into the model can be motivated by a model that explicitly incorporates intermediate inputs. The formulation used to introduce the cost shock into the model is given in Equation 6 and reproduced below (omitting time and location subscripts).

$$ q_C = \frac{w}{A_C} + \phi $$

This formulation can be derived from a model in which production requires both labor, L, and an intermediate input good, I, such as raw cotton. In particular, consider a model in which these inputs are both necessary and must be used in fixed proportions, adjusted for labor productivity $A_C$. The new production function is $X_C = \min(A_C L_C, \beta I_C)$ where $\beta$ determines the ratio of intermediate input to labor. Let $\psi_C$ be the exogenous price of the intermediate input and let $\bar{q}_C$ be the sales price of the finished good. Producer’s f’s optimization problem is then,

$$ \max_{L_C, I_C} \bar{q}_C X_C - w L_C - \psi_C I_C $$

Solving this maximization problem, we obtain the following price charged by perfectly competitive producers in industry C.
Decomposing the intermediate input price into some baseline price $\psi_{C0}$ and some price increase due to the shock $\Delta \psi_C$, we have the following.

$$\tilde{q}_C = \frac{w}{A_C} + \frac{\psi_{C0}}{\beta} + \frac{\Delta \psi_C}{\beta}$$

Now let $\phi = \Delta \psi_C / \beta$ and define $q_c = \tilde{q}_c - \psi_{C0} / \beta$ to obtain the formulation used in Equation 6.

Using a fixed-input proportions production function here may seem somewhat restrictive, but it is a reasonably good approximation of the empirical setting. Given the nature of cotton textile production, it was hard for producers to significantly reduce the share of raw cotton inputs in production, though efforts were made to reduce waste cotton in the production process during the period in which raw cotton prices were high. Note that in this formulation, technological progress acts to reduce the ratio of labor to raw cotton inputs required in production, which also fits the empirical setting well, and increases the flexibility of the production function.

C.2 Proof of Obs. 1

Part 1 – Effect of the shock on industry C in the shock period

Begin by noting that $dq_{CI}/d\phi = 1$. Taking this derivative and reorganizing we obtain the following, where the inequality follows from the fact that $A_{CH} > A_{CF}$ implies $q_{CH} < q_{CF}$.

$$\frac{dL_{CH}}{d\phi} = \frac{E_i q_{CH}^{-\sigma} A_{CH}^{-1}}{(q_{CH}^{1-\sigma} + q_{CF}^{1-\sigma})^2} \left[-q_{CH}^{1-\sigma} + \frac{\sigma - 1}{q_{CF}^{1-\sigma}} - \frac{\sigma}{q_{CF}^{1-\sigma} q_{CH}}\right] < 0$$

Second, we want to show that $d(ln(L_{CH}) - ln(L_{CF}))/d\phi < 0$. We start with the difference in log employment between the two locations.

$$ln(L_{CH}) - ln(L_{CF}) = -\sigma (ln(q_{CH}) - ln(q_{CF})) - (A_{CH} - A_{CF})$$

Taking the derivative gives us the following.

$$d(ln(L_{CH}) - ln(L_{CF}))/d\phi = -\sigma \left[\frac{1}{q_{CH}} - \frac{1}{q_{CF}}\right] < 0$$
C.3 Proof of Obs. 3

We must show that when $\tau^{iC} > 0$ and $A_{CH} > A_{CF}$, then $\frac{dS_{CH}}{d\phi} > \frac{dS_{CF}}{d\phi}$, where we ignore subscripts since all variables are for period $s$. Taking the derivatives, this will be true when,

$$\frac{\tau^{iC}}{L_{CH} + 1} < \frac{dL_{CH}}{d\phi} < \frac{\tau^{iC}}{L_{CF} + 1} < \frac{dL_{CF}}{d\phi}$$

Given that $L_{CH} > L_{CF}$, which follows from $A_{CH} > A_{CF}$ and Equation 3, it will be sufficient to show the following.

$$\frac{dL_{CH}/d\phi}{L_{CH}} < \frac{dL_{CF}/d\phi}{L_{CF}}$$

Using Equations 3 and taking derivatives, this is equivalent to showing,

$$\frac{1}{q_{CH}^{\sigma}} + \frac{1}{q_{CF}^{-1}q_{CH}} > \frac{1}{q_{CF}^{\sigma}} + \frac{1}{q_{CH}^{-1}q_{CF}}$$

Multiplying through by $q_{CF}^{\sigma}$, we obtain the following, where the inequality must hold given that $A_{CH} > A_{CF}$ implies $q_{CH} < q_{CF}$.

$$\left(\frac{q_{CF}}{q_{CH}}\right)^{\sigma} + \left(\frac{q_{CF}}{q_{CH}}\right) > 1 + \left(\frac{q_{CF}}{q_{CH}}\right)^{\sigma-1}$$

D Additional statistical results

D.1 Impact on the cotton textile industry

We have seen that overall output in the cotton textile industry quickly rebounded following the end of the Civil War. Here we explore whether the distribution of this industry across geographic locations experienced long-term changes as a result of the cotton shortage. We begin with Figure 12, which describes cotton textile employment in towns, where towns have been grouped into low, medium, and high groups, based on each town’s 1851 cotton textile employment share (our instrument for the shock intensity). We see that those towns with a large cotton textile production share in 1851 (Blackburn, Bolton, and Preston), which were also those experiencing some of the most severe shock effects during 1861-1865, saw a continued rapid expansion of cotton textile production, though the graph also suggests that the pace of expansion may have slowed somewhat in these towns after 1861. Towns with
a moderate share of initial cotton textile production in employment in 1851 (Manchester, Oldham, and Stockport) show a decline, driven largely by manufacturing being pushed out of Manchester by other commercial activities. Those with a low level of initial cotton textile employment (Yorkshire towns) experience continued growth, albeit from a much lower level. Thus, no clear pattern of geographic redistribution in this industry appears.

Figure 12: Cotton employment in towns grouped by 1851 cotton employment share

Next, we look for long-term effects statistically using an approach similar to that applied to the related industries. In particular, we run a regression where the dependent variable is log employment in each location. The key independent variable is the intensity of the shock in each location. Results for these regressions are presented in Table 14 below. They provide weak (not statistically significant) evidence that growth in the cotton textile industry may have also been slower in more severely impacted towns in the post shock period. This may indicate that the shock had a long-term impact on the cotton textile industry in these locations. However, there are a couple of facts that caution against taking these results too seriously. First, the 1860-1861 period was one of the most successful ever for this industry, which may inflate the 1851-1861 growth estimates while reducing the 1861-1871 estimates. Second, these results may simply indicate that because of its high concentration in high-impact industries, these results may simply indicate that the industry had reached the point of diminishing returns to concentration in these locations. For example, large mills were unlikely to open in the city of Manchester because of the difficulty and expense of finding the amount of space needed for the large modern mills at this time. Instead, mills often preferred to open in smaller surrounding towns where they could still benefit from
their proximity to markets and supporting industries but at lower cost. Third, it may be that the more severely impacted towns experienced broad negative impacts from the shock. Because these regressions involve only one industry, we are unable to control for aggregate town-level changes that may have been caused by the shock.

Table 14: Effects of the shock on the cotton textile industry in each location

<table>
<thead>
<tr>
<th>DV: Industry Log Emp.</th>
<th>DV: Chg. in Industry Log Emp.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Reduced Form</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
</tbody>
</table>

| Shock Int. * Post     | -0.261       | -0.246       | -0.344       |
|                       | (0.172)      | (0.187)      | (0.263)      |

| Shock Int. * TT       | -0.0904      | -0.0821      | -0.115       |
|                       | (0.0746)     | (0.0849)     | (0.115)      |

| Year dummies          | Yes          | Yes          | Yes          |
|                       | Yes          | Yes          | Yes          |
| Observations          | 55           | 55           | 55           |

Robust standard errors in parentheses  *** p<0.01, ** p<0.05, * p<0.1

D.2 First-stage regression results

This section presents first-stage regression results for the main fixed effect and first-differences regressions presented in the main body, as well as the main robustness regressions. As all of these results show, using each locations 1851 cotton textile employment share provides us with a strong instrument for the shock intensity in each location.

Table 15: First stage regression results for IV’s in Table 4

<table>
<thead>
<tr>
<th>Coag Only Reg.</th>
<th>IO Only Reg.</th>
<th>Both Reg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag<em>Shk</em>Post</td>
<td>IO<em>Shk</em>Post</td>
<td>Coag<em>Shk</em>Post</td>
</tr>
<tr>
<td>.7440591***</td>
<td>.7386922***</td>
<td>.7441289***</td>
</tr>
<tr>
<td>(.0340811)</td>
<td>(.0513013)</td>
<td>(.0340234)</td>
</tr>
</tbody>
</table>

| IO* Shk * Post  | Coag*Shk*Post  | (.0075604) |
| .7386922***     | (.0513354)    |
| (.0022852)      | (.7387465***  |

| Observations    | 7,715         | 7,715      | 7,715      |
| F-stat          | 476.64        | 207.33     | 239.77     | 103.69 |

Robust standard errors in parentheses  *** p<0.01, ** p<0.05, * p<0.1
Table 16: First stage regression results for IV’s in Table 6

<table>
<thead>
<tr>
<th>Coag Only Reg.</th>
<th>IO Only Reg.</th>
<th>Both Reg.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag * Shk * Post</td>
<td>0.7440527*** (0.0345327)</td>
<td>0.7441208*** (0.0344749)</td>
</tr>
<tr>
<td>IO * Shk * Post</td>
<td>0.7385605*** (0.0520102)</td>
<td>-0.002227 (0.0326903)</td>
</tr>
<tr>
<td>Obs</td>
<td>6.172</td>
<td>6.172</td>
</tr>
<tr>
<td>F-stat</td>
<td>464.25</td>
<td>201.65</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 17: First stage regression results for IV’s in Table 9 column 2

<table>
<thead>
<tr>
<th>With Liverpool (col 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag * Shock Int. * Post</td>
</tr>
<tr>
<td>IO * Shock Int. * Post</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>F-stat</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 18: First stage regression results for IV’s in Table 9 column 4

<table>
<thead>
<tr>
<th>Alt. Coag. (col 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag * Shock Int. * Post</td>
</tr>
<tr>
<td>IO * Shock Int. * Post</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>F-stat</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Table 19: First stage regression results for IV’s in Table 9 column 6

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag * Shock Int. * Post</td>
<td>0.7445251***</td>
<td>-0.0004399</td>
</tr>
<tr>
<td>(0.0349962)</td>
<td>(0.0080869)</td>
<td></td>
</tr>
<tr>
<td>IO * Shock Int. * Post</td>
<td>-0.0025286</td>
<td>0.7384876***</td>
</tr>
<tr>
<td>(0.0323037)</td>
<td>(0.0512362)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>7,435</td>
<td>7,435</td>
</tr>
<tr>
<td>F-stat</td>
<td>226.72</td>
<td>104.14</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 20: First stage regression results for IV’s in Table 9 column 8

<table>
<thead>
<tr>
<th>Without IO Inds. (col 8)</th>
<th>Coag * Shock Int. * Post</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coag * Shock Int. * Post</td>
<td>0.761904***</td>
</tr>
<tr>
<td>(0.0421449)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,320</td>
</tr>
<tr>
<td>F-stat</td>
<td>326.82</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

D.3 Alternative clustering of standard errors

The results presented in the main text were calculated while clustering standard errors at the industry-location level. This allowed for correlation between the standard errors within each industry-location over time. However, it does not allow for correlation in the standard errors of the same industry across locations, or for different industries in the same location. The motivation for this approach was to cluster at the industry-location level to deal with serial correlation issues while hoping that the inclusion of industry-period and location-period dummy variables reduced correlation among error terms within industries or locations. We can check the robustness of this approach by calculating additional results while clustering at either the industry level or the location level. These approaches will be more restrictive, since they will reduce the number of clusters to 171 industries, or 11 towns, respectively. Table 21 presents these robustness checks. Columns (1)-(4) show results with standard errors clustered at the industry level. Baseline (columns (1) and (3)) and reduced form results (columns (2) and (4)) are included, but IV results are not calculated because of the technical difficulties involved in calculating fixed effect IV results using clustered
standard errors that include multiple units of the panel variable. These columns show that clustering at the industry level does not meaningfully change our results. Columns (5)-(8) present results when standard errors are clustered at the town level for our 11 towns. We can see that in this much more restrictive specification the estimated coefficients are now only marginally statistically significant, though the estimated coefficients continue to show a negative impact that is statistically significant at the 90% confidence level.

Table 21: Checking robustness to alternative clustering of standard errors

<table>
<thead>
<tr>
<th></th>
<th>Clustered by industry</th>
<th>Clustered by location</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Reduced form</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>Coag<em>Shk</em>Post</td>
<td>-0.0486**</td>
<td>-0.0600***</td>
</tr>
<tr>
<td></td>
<td>(0.0223)</td>
<td>(0.0213)</td>
</tr>
<tr>
<td>IO<em>Shk</em>Post</td>
<td>0.0536*</td>
<td>0.0238</td>
</tr>
<tr>
<td></td>
<td>(0.0290)</td>
<td>(0.0354)</td>
</tr>
<tr>
<td>Coag<em>Shk</em>TT</td>
<td>-0.0235**</td>
<td>-0.0287***</td>
</tr>
<tr>
<td></td>
<td>(0.0118)</td>
<td>(0.0109)</td>
</tr>
<tr>
<td>IO<em>Shk</em>TT</td>
<td>0.0183</td>
<td>0.00189</td>
</tr>
<tr>
<td></td>
<td>(0.0132)</td>
<td>(0.0165)</td>
</tr>
<tr>
<td>Obs</td>
<td>7,715</td>
<td>7,715</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses  *** p<0.01, ** p<0.05, * p<0.1