The Mechanics of the Industrial Revolution

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Although there are many competing explanations for the Industrial Revolution, there has been no effort to evaluate them econometrically. This paper analyzes how the very different patterns of growth across the counties of England between the 1760s and 1830s can be explained by a wide range of potential variables. We find that industrialization occurred in areas that began with low wages but high mechanical skills, whereas other variables, such as literacy, banks, and proximity to coal, have little explanatory power. Against the view that living standards were stagnant during the Industrial Revolution, we find that real wages rose sharply in the industrializing north and declined in the previously prosperous south.

I. Introduction

The question of British leadership in the Industrial Revolution remains one of the central topics in economic history as well as in the larger

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literature on the origins and nature of modern economic growth. That literature is enormous, with attributions ranging from geography to institutions and from colonial exploitation to culture, or possibly even luck.[1] One influential interpretation holds that the Industrial Revolution can be explained by induced technological innovation, with cheap coal power being substituted for expensive labor (Allen 2009a). For many contemporaries, by contrast, Britain's success was rooted in its uniquely deep and diverse pool of artisans, in metalworking especially, whose skills could be readily adapted to developing the new machinery and manufacturing processes that began to appear in the mid-eighteenth century.

Despite the importance of the Industrial Revolution, there have been no previous attempts to evaluate these competing explanations econometrically. The purpose of this paper is to test how the very different patterns of industrial growth across the 41 counties of England can be explained by factors including high wages, energy sources, literacy, banks, and, especially, mechanical skills. On the way, we challenge claims that the Industrial Revolution was induced by a desire to substitute cheap steam-powered machinery for expensive workers and that living standards were static at this time.

The technology of the late eighteenth century is often dismissed as having been fairly rudimentary (which raises the question of why it was not invented a good deal earlier). In fact, the two iconic machines of early industrialization—Arkwright's spinning frame, with its intricately meshing train of gears, spindles, and rollers, and Watt's steam engine, with its precisely bored cylinder and complicated valves—were unusually complex technologies by the standards of the time, and each relied on coopting local artisanal skill for its success.

Our approach is to focus on a simple process where the accumulation of artisan skill drives technological progress, in a way that mirrors the historical pattern of early industrialization. Specifically, as transport networks began to improve and English markets integrated from the late seventeenth century onward, regions specialized according to their comparative

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[1] Geographical explanations focus on natural resources, especially coal and iron, and location; institutional explanations highlight the role of the Whig Revolution and, more generally, a probusiness framework of laws and social institutions; cultural explanations refer to respect for science, innovation, and middle-class values; and explanations invoking empire invoke privileged access to raw materials and the slave trade. On luck, see Crafts (1977). Surveys include Mokyr (2009), Jones (2010), Clark (2014), McCloskey (2016), and Crafts (2021). Our emphasis on skills is perhaps closest to Harris (1976) and Berg (1994, 7), who traced Britain's success to "the extraordinary industry and inventiveness of her manufacturing people."

advantage. This meant that areas of poor agricultural potential (reflected in their low wages) increasingly specialized in manufacturing activities. Naturally, many of these protoindustrial activities, such as making nails or low-quality textiles, required only rudimentary skills and offered no possibilities of technological advances.

However, a few forms of manufacturing—especially in exacting forms of metalwork such as watchmaking, iron founding, and toolmaking—created pools of skilled and versatile workers, artisans whose skills could be readily be adapted and transferred to the increasingly sophisticated machinery and manufacturing processes of the early Industrial Revolution. This simple framework leads to the specific empirical prediction that successful industrialization relied on existing concentrations of suitable skills and that these concentrations were to be found primarily in low-wage areas already specializing in technologically demanding production, in metalworking especially.

The prediction that low-wage areas should be the ones that industrialized runs directly counter to the influential argument of Allen (2009a) that the British Industrial Revolution involved a substitution of steam power for labor.[2] This claim is historically questionable on several counts. Certainly, unskilled English laborers enjoyed considerably higher wages than their French counterparts, but, because they were stronger and better fed as a result, they were proportionately more productive: high wages need not mean expensive labor (Kelly, Mokyr, and Ó Gráda 2014). Moreover, when it comes to the skilled artisans who were the real drivers of the Industrial Revolution, it was France that was the high-wage economy, as shown by the thousands of British artisans who migrated there after 1815 to set up railways, cotton mills, and ironworks (Bensimon 2011).

Turning to England, we show below that it was the low-wage north that mechanized, whereas the high-wage regions in the south that had dominated the textile industry for centuries lacked the technical skills to adopt the new machinery and slid into terminal decline. As a result, living standards rose substantially in the north, overtaking the previously prosperous south, where real wages fell markedly. The widespread notion that average national living standards were static during the Industrial Revolution (Feinstein 1998) is simply a statistical artifact of aggregating two regions that were moving in sharply opposite directions.

Moving on from expensive labor, the claim that the mechanization of the textile industry depended on steam power is also inaccurate. Early steam engines were complicated, expensive, and unreliable contraptions, which meant that textile machinery was powered wherever possible by

[2] Criticisms of these data and methodology include Mokyr (2009, 267–72), Kelly, Mokyr, and Ó Gráda (2014), Stephenson (2018), Humphries and Schneider (2019), and Crafts (2021).

water. Von Tunzelmann (1978, 295) estimates that as late as the 1820s, when most weaving was still done by hand, the cotton industry derived about as much energy from human muscle as from coal.

Strikingly, the fact that the early textile industry made little use of coal made it highly unusual among British industries of the time. By 1750, the British economy was already distinguished by the way that almost every industrial process involving the transformation of materials used coal as a source of heat (as opposed to motive power), in contrast to the wood and charcoal employed elsewhere (Harris 1976). For centuries, coal had been used to work iron in forges, but a decisive breakthrough came with the appearance of heat-reflecting ("reverberatory") furnaces in the late sixteenth century. These provided a general-purpose technology to produce clean heat from contaminating coal that came to be applied to an increasing range of industrial processes, culminating in wrought iron in the 1780s.

In summary, then, the analysis suggests that mechanized textile production in the mid-nineteenth century would be located in regions that combined low wages and high mechanical skills in the mid-eighteenth century and that widespread ironworking would be found in regions that had been accumulating skill in coal-based metallurgy over centuries. To test these predictions, we analyze the patterns of male employment across the 41 counties of England (although the Industrial Revolution was very much a British phenomenon, data for Scotland and Wales are sparse, for early wages in particular).

Our regressions use spatial data, and such regressions often generate spuriously high t-statistics, both because the included variables display strong directional trends and because nearby points closely resemble each other, leading to effective sample sizes that are smaller than they appear. The latter issue has received considerable attention in econometrics, starting with the kernel adjustment of Conley (1999). Later corrections include large-cluster estimators (Ibragimov and Müller 2010; Bester et al. 2016; Canay, Romano, and Shaikh 2017) and Müller and Watson (2021) principal components. Unfortunately, different adjustments commonly return significance levels that can vary over an order of magnitude. A Canay, Romano, and Shaikh (CRS) correction with, say, eight clusters will often not only differ markedly from a Müller and Watson (MW) correction that imposes an average correlation of 0.01 but each, in turn, will also differ entirely from a CRS correction with 12 clusters or an MW correction with a correlation of 0.05.

In this paper, we introduce a simple way to circumvent these difficulties by employing a semiparametric regression that incorporates a spatial smoothing term. Semiparametric regressions go back to Engle et al. (1986), who added to linear regressions a smoothing spline that optimally adapted itself to fit time trends of unknown functional form. Despite their elegance, simplicity, and power, semiparametric regressions never took off in economics. However, they have continued to be actively developed in statistics, under the name "generalized additive models" (Wood 2017), and have become popular in machine learning as estimators that are often almost as powerful as black-box techniques but whose results are immediately interpretable (James et al. 2021, 289–310). Where Engle et al. (1986) added a one-dimensional spline in time, we add a two-dimensional one in longitude and latitude. This allows us to separate out the spatial structure of the regression as a nuisance variable and then carry out standard inference on the parameters that interest us.

For textiles, our dependent variable is the share of male employment in textile production in 1831. To measure the supply of preexisting skill, we use data from the 1851 census on the occupations of workers aged 60 and above born in each county: men who would mostly have been apprenticed in the late 1790s to masters trained by a previous generation. We find that the percentage of men working as mechanics and toolmakers, alongside low wages in the 1760s, explains 70% of the variation in textile employment in 1831. The effect sizes are substantial: the supply of skilled workers has an elasticity of 2, and wages have an elasticity of −5. Given the limited use of steam in textiles, proximity to coal has as little explanatory power, as we would expect.

Some explanations of the Industrial Revolution have emphasized schooling, property rights, or financial markets. To assess the importance of these factors, we add estimates of literacy and the number of booksellers for human capital and the number of attorneys for security of property rights, as well as the density of local banks to assess the importance of access to external finance. The contribution of these variables is negligible.

The natural reservation about these regressions is that the supply of mechanical skill in the 1790s might have been endogenous: new textile industries could have attracted skilled workers, rather than vice versa. To control for this, we instrument the employment of skilled workers with the cost of becoming a watchmaking apprentice between 1750 and 1779. The identification strategy is that there appears to be no direct path connecting the cost of becoming a skilled watchmaker to the number of factory hands laboring in textile mills several generations later. The apprentice fee instrument, largely supply driven, is strongly negatively correlated with mechanical skill, and the estimated elasticities are little changed from ordinary least squares (OLS).

Turning to ironworking, we analyze employment in 1851. Although a nearby supply of coal for smelting and forging was necessary for an industry to emerge, it was not sufficient. Instead, heavy metallurgy concentrated in areas around Birmingham that had been accumulating expertise in the iron trades since the seventeenth century (Berg 1994). Explanatory power is again high.

By way of a control, we analyze the employment patterns of large traditional sectors where technology was fairly static at this time: food processing, woodworking, garments, and shoes (as Clapham 1939 [169] observed, England in 1831 had many more cobblers than coal miners). In these sectors, the variables that drive the regressions for the progressive textile and iron manufactures have little explanatory power.

The rest of the paper is as follows. In section II, we show the role of artisanal skill in developing some of the best-known technologies of the Industrial Revolution, the role of coal as a source of heat for metalworking, and the historical supply of skilled workers. A simple specific-factors framework for understanding British industrialization is given in section III, and section IV examines the patterns of growth across regions. Sections V–VII describe our regression results for textiles, metals, and traditional industries, respectively, and section VIII concludes.

II. Skills and the Industrial Revolution

For contemporary observers, the successful development of Britain's factory system stemmed from an abundance of long-existing artisan skills combined to new purposes. This combination can be seen in late-eighteenth century insurance contracts where the value of a factory is divided into its "millwright's work," or power, and its "clockmaker's work," or machinery.[3] Here, we briefly discuss the contribution of Lancashire watchmakers to the development of early textile machinery and the role of the Birmingham metal trades in developing Watt's steam engine.[4]

A. Textile Machinery

Despite the widespread view that the technology of textile production during the Industrial Revolution required little advanced skill or formal knowledge, much of it was anything but simple. Hargreaves's spinning jenny, the first major advance in cotton spinning, was indeed a rudimentary, hand-powered machine that could be built by any competent local carpenter.[5] However, one of the leading Manchester cotton spinners, John Kennedy, recalled in 1815 that with the appearance in 1789 of Arkwright's

[3] For instance, in 1799 the textile mill of Bissett and Co. was insured for £2,950, made up of £350 for millwright's work, £950 for clockmaker's work, and the remainder for buildings and stock (Tann 1970, 33).

[4] Another important group, millwrights, is examined by Mokyr, Sarid, and van der Beek (2022).

[5] Allen (2009b) views the jenny, which he deems "not rocket science," as encapsulating the "Industrial Revolution in miniature." McCloskey (2010, 355–65) too, subscribes to the "practical tinkerers" view. While this was an apt description of some famous inventors, many others, such as William Strutt, John Smeaton, William Murdoch, were connected to practical science and advanced engineering.

water frame and its intricately meshing metal rollers, spindles, and gearing, "a higher class of mechanics, such as watch and clock-makers, whitesmiths, and mathematical instrument-makers began to be wanted; and, in a short time, a wide field was opened for the application of their more accurate and scientific mechanism" (Kennedy 1819, 124).[6] A particular advantage enjoyed by the early Lancashire cotton industry was that its easy access to the skills of a large agglomeration of watchmakers and watch-tool makers, whose highly developed division of labor and specialized tools made them Adam Smith's chosen example of technological progress (Allen 2009a, 205–6; Kelly and Ó Gráda 2016).[7]

The soft brass gears of early textile machines were soon replaced by durable cast iron ones. This meant that their construction was first taken over by iron founders and makers of large clocks, whose facility with heavy lathes and gear cutters readily scaled from brass to iron (Kelly and Ó Gráda 2022). Rapidly, however, the large scale of the cotton industry led to the emergence of firms of specialized machine builders, but the gearing of a textile machine was still invariably known as its clockwork.[8]

B. Steam Engines

Just as Lancashire's agglomeration of watchmakers was vital to the successful development of powered textile machinery, so was the concentration of metal trades in Birmingham to that of the steam engine. Although Newcomen had come up with the idea of an atmospheric engine before 1710 in Cornwall, he could not get it to work for its intended purpose of pumping mines without the help of "ingenious Workmen" from Birmingham (Desaguliers 1744, 533). Birmingham metalworking was equally instrumental to the success of Watt's engine. Although Watt had built his first experimental engine in Scotland in 1768, his progress was frustrated by its flimsy, poorly fitting cylinder until, in 1774, he moved to Boulton's large metal works in Birmingham.

Although Britain started with a uniquely large and flexible supply of artisans, the rapid rise in demand for their services in the late eighteenth century created notable skill shortages. Predictably, some of the severest shortages of skills were suffered by Boulton and Watt, as the producers of the most complicated large machine of its time, resulting in unreliable engines,

[6] This view is supported by the large number of newspaper advertisements from the 1770s onward, looking for smiths, watchmakers, and toolmakers (Musson and Robinson 1969, 427–58).

[7] When Arkwright, assisted by a local watchmaker John Kay, began to build the first spinning frame, a local engineer "agreed to lend Kay a smith and watch-tool maker, to make the heavier part of the engine, and Kay undertook to make the clockmaker's part of it" (Baines 1835, 150).

[8] The skills that British artisans brought to the cotton industry were more than just mechanical aptitude: skilled chemists were vital in the development of bleaching powder and soda making (Christie 2018).

long delivery lags, and a complete absence of after-sales service (Tann 1970, 83). To compensate, Boulton and Watt pioneered a form of industrial organization of unusual sophistication and complexity, where a standardized range of engines sizes (allowing a stock of spare parts to be kept on hand for customers experiencing breakdowns) was made on a systematic production line with a detailed and explicit division of labor (Roll 1930, 179–84).

C. *Coal and Heat Skills: Metallurgy*

Against the widespread belief that Britain's large coal resources gave it a cheap source of motive power for early textile machinery, in reality coal's early contribution was minor. Kanefsky (1979, 338) estimated that water power accounted for 70% of industrial power in 1800, compared with 20% for coal, and was overtaken by coal only around 1830.[9] Cotton was woven almost entirely by hand until the 1820s, and von Tunzelmann (1978, 179) estimates that as late as 1800 a quarter, at most, of Lancashire cotton was spun using steam.

The reasons are clear: besides paying for fuel (on top of heavy annual royalties to Boulton and Watt), water cost only about one-quarter as much per horsepower as steam to install around 1790 (Chapman 1970, 241); the efficiency of water wheels improved dramatically through the experimental work of Smeaton and others; and the lifetime of new iron water wheels was measured in decades, compared with years for steam. Steam was adopted in the early nineteenth century only when the reliability and efficiency of the engines was improved, machinery was increasingly made of iron rather than wood, and suitable sites for water power were becoming scarce.

However, the fact that spinning and weaving relied so little on coal before the early nineteenth century made them highly unusual among British industries at the time. As Harris (1976) noted, the distinguishing feature of Britain's economy in the early eighteenth century was its almost exclusive reliance on coal as a source of industrial heat, rather than the wood or charcoal employed elsewhere.

Coal had been used since the middle ages for boiling water for brewing beer, extracting salt, cleaning raw wool, and heating dye for textiles. For metalworking, the first important use of coal from medieval times was for working iron in forges. However, for other applications, although coal offered a cheap source of intense heat, it was very polluting, contaminating any materials it came in contact with.[10]

[9] It is notable that Wrigley (1988)—who popularized the idea of the British Industrial Revolution as a transition from an inherently limited "advanced organic economy" of wood and animal power to one powered by inorganic energy in the form of coal—mentions water power only twice in passing (pp. 27 and 75), and it is absent from the index.

[10] Abraham Darby came up with the partial solution of using degassed coal, or coke, that could be used to make cast iron, but demand for this was limited at first (Hyde 1977).

The vital generic technology for using coal as a clean source of heat came in the form of the reverberatory furnace, where heat from coal gases was reflected downward from a domed roof. As experience and competence in the use of these furnaces grew, coal spread from smelting copper, in the early seventeenth century, to glassmaking and pottery and then, in the 1740s, to making steel in clay crucibles. Cort's 1783 puddling process of smelting wrought iron in a reverberatory furnace was less the revolutionary substitution of mineral for organic energy that it is often portrayed to be, but "one more conversion" of fuel from wood to coal. It was for this lack of originality that Cort's patent was revoked (Harris 1988, 26).

The growth of technological competence, then, was a centuries-old evolution where the skills developed in mastering one process were applied to other, more demanding processes. Expertise grew in designing and building furnaces, making refractory bricks and crucibles, and maintaining exact temperatures, portfolios of interlocking artisanal skills that could not be readily exported piecemeal.

Many of the tools, instruments, and machines that typified the Industrial Revolution required high-quality iron and steel. Birmingham was known for its extensive variety of metal trades, ranging from forging and casting in the neighboring Black Country to more intricate work such as guns, clocks, locks, and mass-produced "toys" (decorative metal goods). Sheffield, already producing the best files in Europe by 1700 (Harris 1998, 95), was the birthplace of crucible steel, which gave Britain a unique advantage in the high-quality metalworking tools that were increasingly in demand for shaping machine parts.

D. The Market for Artisan Skill

Naturally, England owed its large supply of proficient metalworking craftsmen to many more things than a fortuitous abundance of coal. On the supply side, the relatively limited power of guilds meant that rapidly growing sectors could swiftly attract extra apprentices (Ben Zeev, Mokyr, and van der Beek 2017).[11] The impact of apprenticeship institutions on the transmission of knowledge is demonstrated by de la Croix, Doepke, and Mokyr (2018). On the demand side, from the mid-seventeenth century the English were becoming an increasingly "polite and commercial people,"[12] with rising prosperity caused by and causing urban expansion, growing overseas trade, intensified agriculture, and the improved transportation networks that made regional specialization possible.

Britain's relatively large "middling class" meant that the demand for better-quality upmarket goods, many involving complicated manufacturing,

[11] See also Leunig, Minns, and Wallis (2012) and Ogilvie (2019, chap. 9).

[12] Paul Langford (in *A Polite and Commercial People: England 1727–1783*, Oxford: Oxford Univ. Press, 1988) attributes this expression to Judge William Blackstone.

was on average higher there than elsewhere. The relative affluence of the working class, shown in such things as the quality of their everyday clothes, was often noted (Styles 2007, 13), and the fairly decent quality of their diets resulted in considerably taller, stronger, and more productive workers than elsewhere. This meant that although English workers did earn wages that were substantially higher than their French counterparts, they were also more productive: high wages did not necessarily mean expensive labor (Kelly, Mokyr, and Ó Gráda 2014).[13]

The need for a region to be close to large concentrations of diverse mechanical skill in order to industrialize successfully suggests a possible answer to a central question in the economic history of the Industrial Revolution: Why did some areas of large-scale cottage industry ("protoindustry"), such as northern and midland England, go on to industrialize successfully, when others, such as the west of England, southern Ireland, and northern France, failed (Coleman 1983)? The decisive characteristic that distinguished winners from losers, we argue, was a supply of mechanical expertise, a claim that we test directly in section IV.

III. Regional Integration and the Accumulation of Skill

From the early eighteenth century, market integration in England was driven by the rapid growth of transportation networks, with rivers made navigable and roads, many previously usable only by packhorses, being turnpiked. Just as important for a large island, but often overlooked, was the rapid expansion of coastal shipping (Armstrong 1987).

These large improvements in transport infrastructure allowed regions to specialize according to their comparative advantage. Specifically, areas with poor soil began to specialize in manufacturing activities and to import food. This is most easily understood in a simple specific-factors model where falling food prices reallocate unskilled labor to industry and increase the incomes of skilled factors specific to that sector; see figure 1.

In thinking about the British economy on the eve of the Industrial Revolution, it is useful to divide it into two regions, North and South. Each region has two sectors, agriculture and manufacturing, and each sector has a specific factor: fertile land for agriculture and skilled artisans for manufacturing. There is a common pool of unskilled workers who can work in either sector. We suppose that the North has less fertile land and a larger supply of skilled artisans than the South. There is assumed to be no mobility of workers between regions, which again is historically fairly accurate because most internal migration in an era before railways occurred over short distances (Redford 1964).

[13] At the French firms of Charenton and Le Creuzot, English workers were paid about 50% more than their French counterparts (Belhoste and Woronoff 2005, 90–91).

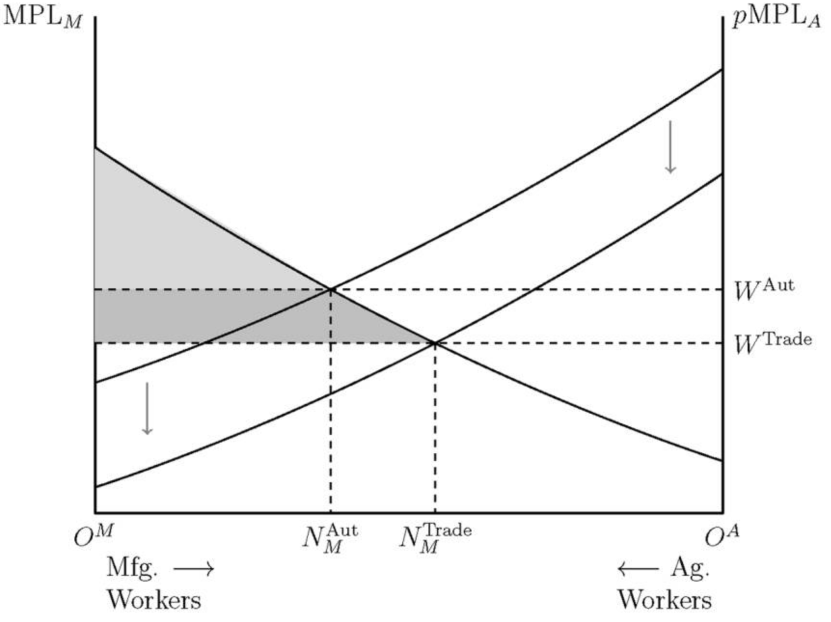

FIG. 1.—A fall in the relative price of agricultural goods caused by market integration leads areas with poor soil to specialize in various manufacturing activities. Some of these activities have the potential to generate new skills of the sort that underlay British industrialization.

Growing integration leads low-wage areas with large endowments of skilled workers to specialize in manufacturing, while more prosperous areas with high agricultural potential deindustrialize.[14] We begin with a textbook diagram in figure 1 (depicting the North), where the supply of unskilled labor gives the length of the x-axis and the labor demand of each sector is drawn on opposite sides so that equilibrium wage and the employment levels of each sector are given by the intersection of the curves.

As transportation costs fall and trade between regions increases, the relative price of agricultural goods in the North falls, causing the labor demand curve for agriculture to fall. This causes the output of manufactures to rise, along with the income of skilled artisans, given by the triangle between the equilibrium wage and labor demand curves. At the same time, the South deindustrializes and increasingly specializes in agriculture.[15]

The income of skilled artisans will rise further if there is an influx of unskilled workers, who are a complementary input to skilled workers in

[14] The classic historical account of this is by Jones (1968). See also Jones (2010).

[15] This simple discussion of historical specialization mirrors the modern literature on structural transformation (for a review, see Herrendorf, Rogerson, and Valentinyi 2014), such as Moscona's (2019) finding that the Green Revolution reduced urbanization in areas where agricultural productivity rose sharply.

industrial production (e.g., the immigration of the Irish settling in the new industrial cities after 1800; Clapham 1939, 59–62). This raises their numbers as well, as parents have more of an incentive to apprentice their sons into skilled occupations.

The result is that a region with poor agricultural productivity will accumulate increasing numbers of artisans with specific manufacturing skills (besides offering cheap labor for new manufacturing enterprises), and some of these skills may be conducive to the subsequent development of new industrial technology of the sort that occurred historically in parts of England.[16] We test these predictions below.

IV. The Great Reversal and the Living-Standards Puzzle: England 1760–1830

Preindustrial England fell into three regions. The first was the prosperous, high-wage agricultural region of the south and east, which for centuries had been the heartland of England's main industry, the manufacture of woolen cloth. Next was the urban giant of London, which, as well as being a port, was a major industrial center. By 1750, it contained over 10% of England's population and was the largest city in Europe (Jones 1968; Wrigley 2010, 61).

The final region was the upland north and west. Despite low wages reflecting the region's poor agricultural potential, its population had been growing rapidly since the seventeenth century in response to the widespread nonagricultural employment opportunities offered by outwork and small-scale cottage industry. As well as fast-flowing streams to provide water power, this region had ample supplies of "cheap and amenable female and child labour" (Humphries 2013, 693) that eventually became a vital input into the early factories of the Industrial Revolution, combined with a fairly well-nourished population for undertaking heavy physical labor (Horrell and Oxley 2012). Above all, this region also possessed a flexible supply of highly competent workers with useful mechanical skills—clockmakers, mechanics, toolmakers—who would play a key role during the Industrial Revolution and several of whom would become inventors and factory owners in their own right (Cookson 2018).

A. *The Great Reversal*

Figure 2 shows a map of England where the counties are rescaled in proportion to their aggregate labor income: the wage of agricultural laborers times population. Counties are shaded according to the wage rates of

[16] In the working-paper version, we analyze a process where market integration leads to a mutually reinforcing growth of skill and production technology through parental investment and learning by doing and show how this process can lead to a sudden transition from a low-technology-skills steady state to a high-skills one.

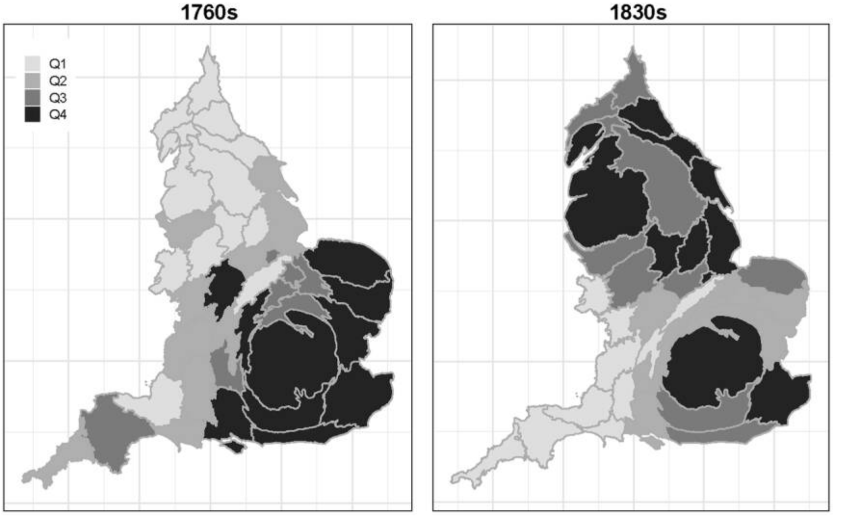

FIG. 2.—Cartograms of England in the 1760s and 1830s. The area of each county is scaled in proportion to its aggregate labor income (wage times population), and shaded according to its wage rate.

agricultural laborers in each period. Given the absence of any restrictions on occupational mobility, these are likely to have been close to the wages earned by unskilled laborers in other sectors.

Figure 2 shows that in the 1760s, the English economy was still dominated by London and its environs and southern wages were higher than northern ones, reflecting their higher agricultural productivity. By the 1830s, we observe what can only be called a great reversal: northern counties that were in the bottom quartile of wages are now in the top one, and the aggregate income of the textile areas of Lancashire and West Yorkshire had become as large as London's. At the same time, manufacturing in the south, London and its environs excepted, sharply declined, a phenomenon described by Jones (2010, 47–50) as "the anomaly of the South." While these changes took two full generations to be completed, they underline that the Industrial Revolution, while perhaps not as dramatic as the word "revolution" conjures up, brought about radical structural changes in the economic geography of Britain.

B. The Standard-of-Living Puzzle

This analysis also sheds light on one of the more durable puzzles of the British Industrial Revolution, the supposed failure of real wages to increase appreciably despite rapid technological progress and industrialization (Feinstein 1998; Mokyr 1999, 113–16). Figure 2 shows that the puzzle is in large measure a statistical artifact caused by looking at national wages rather than regional ones. National real wages were indeed static between 1760 and 1830: weighted by population, the average national money wage rose by 50%, as did the national consumer price index estimated by Clark (2011). However, this disguises the 80%–90% rise in nominal wages in industrializing counties, compared with only 15%–25% in agricultural ones, so that northern wages not only caught up to southern ones but overtook them.

Wage dispersion remained constant, with a coefficient of variation of 13% in both the 1760s and 1830s: the poorest counties in the 1760s had wages that were 70% of the highest ones (for comparison, average French wages at the time were 80% of English ones). One possible caveat here is that differences in the cost of living might account for some of the regional variation in wages. Yet Crafts (1986, 68) and Hunt (1986) have shown that regional cost-of-living differences in the 1840s were minor. What of earlier? Frederic Eden's *The State of the Poor* (1797) is a comprehensive source on regional price variations: it indicates little difference between the cost of provisions in northern and southern counties in the mid-1790s; if anything, prices seem to have been slightly higher in the north.

The differential labor demand that drove these wage rises led to very different patterns of population growth. Between 1761 and 1831, the population of the depressed agricultural counties in the south and east grew only 25%–33%, whereas that of the industrial counties and those around London more than doubled, with that of Lancashire more than quadrupling.

V. Regression Results: Textiles

Although the regional specialization model outlined above is extremely simple, it makes the very specific and testable prediction that areas that industrialize successfully will have had poor agricultural potential combined with high endowments of skills that could be applied to new textile manufacturing activities (fig. 3).

A. Data

The specific-factors model predicts that before the growth of industry, low agricultural potential translated into low wages. This turns out to be the case for England. For agricultural wages in the 1760s, the correlation with the median county level of suitability for wheat, estimated by the United Nations Food and Agriculture Organization, is 0.5; that with the average land tax per acre in 1707 (leaving out London) is 0.6; and their correlation with the age of the dominant rock type in each county—hard, ancient rock weathers into less fertile soil—is 0.7. We report results below using agricultural wages as the explanatory variable, but using any of these three measures of agricultural potential gives similar results.

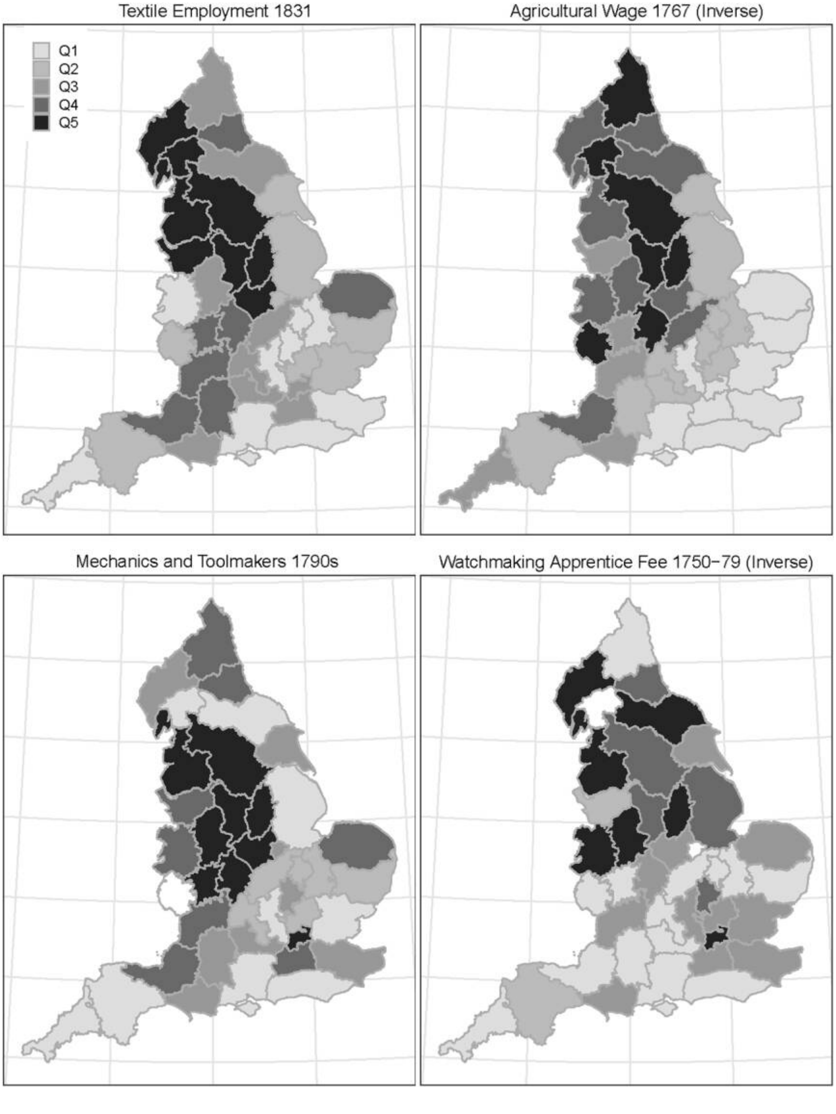

FIG. 3.—County levels, shaded by quintile, of textile employment in 1831, the inverse wage of agricultural laborers, the share of mechanics and toolmakers in the labor force in the 1790s, and the inverse cost of becoming a watchmaking apprentice. The paper predicts that successful textile areas in the nineteenth century will have had low wages and high levels of mechanical skill in the eighteenth century. The cost of becoming a watchmaking apprentice is used as an instrument to deal with potential issues of endogeneity and measurement error in the mechanics and toolmakers variable.

Although it is straightforward to measure wages and agricultural potential, the challenge comes in measuring the availability of skill at the beginnings of industrialization. We do have detailed data on the supply of one type of skilled artisan in the mid-eighteenth century: watch- and clockmakers, where the records of the London Watchmaker's Company (guild) detail every one of its apprentices during the eighteenth century (Moore 2003). However, as Cummins and Ó Gráda (2022) demonstrate, roughly half of English watchmakers never apprenticed to the guild (and about 80% in the main watchmaking region, Lancashire), making this a potentially unreliable measure.

To test our hypotheses, we instead take advantage of the fact that the 1851 census details the numbers of workers in each occupation broken down by age. By examining elderly men (aged 60 and over, most of whom would have been apprenticed around age 14 in the late 1790s), we can get an idea of the geographical availability of skill at an earlier stage of the Industrial Revolution.[17] For nearly every county and every skill, the number of these men with a particular skill residing in a given area closely matches the cohort size of men with the skill born in that county, suggesting that most of these skilled workers were apprenticed locally and that intercounty migration does not confound the analysis.[18]

We focus on the share of men over 60 born in each county who had potentially useful skills. Specifically, we look at blacksmiths, millwrights (both traditional skills), watch- and instrument makers, gunsmiths and locksmiths, toolmakers, sheet-metal workers, and mechanics. These last workers made, assembled, and maintained the machinery we associate with the Industrial Revolution.

Given their historical importance for early industrialization, it might seem surprising at first that the number of watchmakers and lock- and gunsmiths has little explanatory power. It is important to remember, however, that specialized industrial skills were transformed and adapted rapidly: many of the men in our sample may have been trained by masters who started out as watch-tool makers or millwrights, but by 1851 they were making a living as industrial-tool makers or machine builders (Mokyr, Sarid, and van der Beek 2022). Terms such as millwright and blacksmith, moreover, by 1851 meant different things in different places. In agricultural areas, they were largely engaged in traditional practices of maintaining water mills (millwrights) and making farm implements and shoeing horses (blacksmiths), whereas in industrial areas, millwrights were increasingly morphing into engineers and blacksmiths forged machinery parts.

[17] Using men aged 50 and over gives practically identical results.

[18] Historical research finds that most factory workers were recruited from the rural hinterland surrounding the new industrial centers (Redford 1964; Anderson 1971).

We have data for textile employment from two censuses, 1831 and 1851. What we observe in table 1 is that the distribution of textile employment is largely unchanged during this time: the regression results are very similar, except that the coefficients in 1851 are around 1 standard deviation smaller.

The broad patterns of the data are shown in figure 4, which plots textile employment share in 1851 against the supply of mechanical skill in the 1790s and the agricultural wage in the 1760s. It is immediately evident that successful regions were those that had combined low wages with high mechanical skills allowing them to adopt new machinery.

The points for Gloucestershire (GLC) and West Yorkshire (YWR) are particularly revealing. In the mid-eighteenth century, Gloucestershire and the west of England dominated the English woolen textile industry (other centers, such as Norfolk and Suffolk, had already started to decline), but it failed to mechanize and by 1851 had become a comparative backwater, with the industry dominated by the factories of West Yorkshire. Although the West Country around Gloucestershire was actually a large producer of charcoal iron, in the absence of coal this iron had to be sent to be worked in Birmingham, so that the region failed to develop the skilled labor that its textile industry needed to mechanize successfully.[19] Similarly, Jones (2010, 86) observes that the industrial decline of the west of England owed little to coal prices. Coal prices were indeed one-third higher in the west of England, compared with those in Yorkshire, but coal accounted for only a small fraction of production cost.[20]

B. OLS Results

Table 1 gives the results of regressing textile employment in 1831 and 1851 on a variety of possible explanatory variables. First is mechanical skill in the 1790s, which we treat as exogenous for now. Next, we have agricultural wages, to test whether high wages in the 1760s drove regions to substitute machinery for expensive labor or whether regions of poor agricultural potential and low wages came to specialize in manufacturing as national markets integrated.

Given the importance of market integration to our story, we include the size of the potential market (measured as the product of 1760s wages and 1750 population, with weights declining with the square of distance), emphasized by Crafts and Wolf (2014). In addition, we include proximity to coalfields and water flow. Other factors are considered below.

[19] In the words of its leading historian, "With no large coalfield nearby, no heavy iron or engineering industries, and no other local industry requiring precision engineering, the area lacked a pool of skilled labour to draw upon" (Tann 1974).

[20] Even in 1870, the average cotton mill was driven by a 120-horsepower engine (less than most small cars); Samuel (1977, table 1).

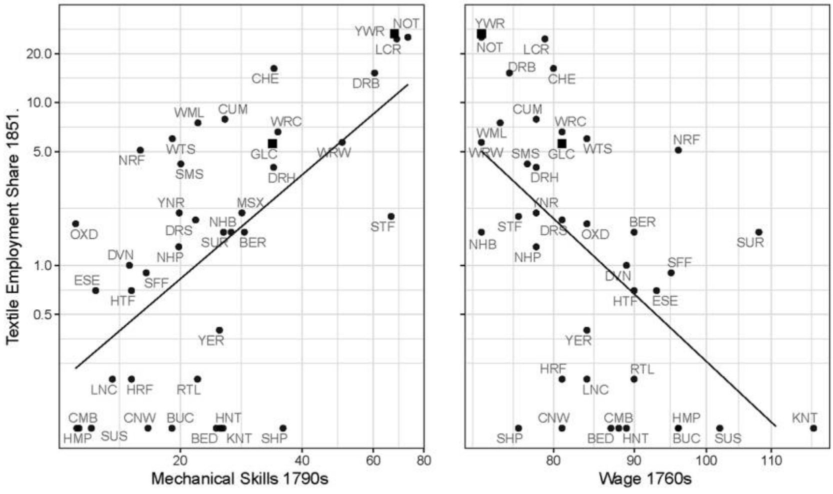

FIG. 4.—Supply of mechanical skill in the 1790s and agricultural wages in the 1760s versus the percentage of males employed in textiles in 1851; logarithmic axes. Note how the decline of Gloucestershire (GLC; the dominant woolen textile center in the mid-eighteenth century) and the rise of West Yorkshire (YWR) can be predicted by their respective supplies of mechanical skills in the 1790s. Full county names corresponding to these abbreviations can be found in the replication files.

In any regression using spatial data, there is a real possibility that the results are spurious artifacts of underestimating standard errors or fitting directional trends. There are many standard error corrections that attempt to control for the fact that the effective sample size can be smaller than it appears because many observations closely resemble their neighbors. These include the Conley (1999) kernel adjustment; the large-cluster procedures of Ibragimov and Müller (2010), Bester, Conley, and Hansen (2011), and Canay, Romano, and Shaikh (2017); and the principal components approach of Müller and Watson (2021). However, as we demonstrate in appendix A, these corrections commonly return significance levels that not only vary widely between estimators (sometimes by an order of magnitude or more) but are also often highly sensitive to the assumed value of their tuning parameters. For these adjustments to be useful, they require, moreover, that low-frequency spatial trends have already been properly removed from the regression to ensure unbiased coefficient estimates.

Given the infeasibility of current approaches to spatial regressions, we adopt instead a simple semiparametric approach in the spirit of Engle et al. (1986). Alongside the explanatory variables of interest, we add a thin-plate regression spline in longitude and latitude that optimally absorbs the spatial structure—both low-frequency directional trends and local correlation—and allows us to proceed with standard inference techniques. We outline the approach in appendix A and provide Monte Carlos to demonstrate its accuracy.

TABLE 1
TEXTILE EMPLOYMENT IN 1831 AND 1851: SEMIPARAMETRIC SPATIAL REGRESSIONS
(41 Observations)

	Dependent Variable: Share of Men Employed in Textiles					
	1831			1851		
	(1)	(2)	(3)	(4)	(5)	(6)
Skills, 1790s	2.022	2.466	2.020	1.151	1.079	1.007
	(.503)	(.668)	(.511)	(.398)	(.532)	(.377)
Wage, 1760s	−4.776	−5.402	−4.783	−3.035	−3.004	−1.623
	(2.742)	(2.817)	(2.937)	(2.109)	(2.138)	(2.056)
Market potential, 1750	.712	.592	.712	.503	.514	.403
	(.301)	(.320)	(.306)	(.217)	(.227)	(.209)
Distance to coal		.720			−.127	
		(.685)			(.650)	
Water power			.001			−.664
			(.425)			(.348)
Adjusted R^2	.684	.695	.676	.813	.810	.865
AIC	131.1	130.6	132.9	88.7	89.5	74.3
S(lon,lat)	.641	.534	.768	.070	.076	.013

NOTE.—Dependent variable is the employment share of textiles among all males over 20 in 1831 and among males aged 20–29 in 1851. Semiparametric regressions with a thin-plate spline in longitude and latitude: S(lon, lat) gives the approximate significance. Standard errors are in parentheses. Regressions include a dummy in 1831 for Shropshire and a dummy in 1851 for Staffordshire. All other variables are in logs. AIC = Akaike information criterion.

What table 1 indicates is that the growth of textile production occurred in areas with vigorous supplies of skilled metalworkers and low wages, alongside access to substantial markets. The size of the coefficients is notable: the elasticity of textile employment in 1831 with respect to skill supply is in the region of 2, while wages have an elasticity of around −5, although the associated standard error is large. Market potential has a considerably smaller elasticity of 0.6. Given the limited use of steam in textiles, proximity to coal has little explanatory power. It is increasingly understood that the arbitrary benchmark of 5% significance often tells less about the importance of a variable than about how precisely it has been estimated. For 1851, the elasticity of employment with respect to skill has fallen to around 1, and the wage elasticity has declined somewhat, to −3.

The S(lat, lon) term gives the approximate significance level of the penalized spline in latitude and longitude. For the 1831 regressions this has little explanatory power, whereas for 1851 there is a somewhat stronger spatial pattern to the observations. If we compare the semiparametric estimates in table 1 with the OLS ones reported in table 4, there is little material difference between them. One potential complication with semiparametric estimation is that any spatial component in an explanatory variable will get confounded with the spatial component in the regression equation, but this can be handled by a standard two-step procedure outlined in appendix A. The two-step estimates do not differ noticeably from the unadjusted semiparametric ones and are not reported here.

Table 2 considers a variety of other factors often mentioned in discussions of the causes of the Industrial Revolution, adding extra variables to the base regressions in the first columns of table 1. These are literacy around 1800 and booksellers per capita in 1761, as measures of human capital. The number of lawyers per capita in 1730, which largely reflects the intensity of local land enclosures (Aylett 1987), is added as a measure of the security and easy transfer of property rights.

Population density is the ratio of population in 1700 to agricultural land, reflecting the hypothesis that areas of cottage industry that were able to support large nonagricultural populations developed the skills and attitudes that subsequently drove industrialization (Coleman 1983). If our argument is correct, protoindustrial areas that lacked mechanical skills failed to industrialize, so this variable should have no impact.

Finally, we include the number of country banks in the 1790s. Quite apart from the need for trade credit, if industrialization was driven by a desire to replace expensive workers with machinery, this investment would have been facilitated in areas with extensive banking networks (Pressnell 1956; Neal 1994). The reported coefficients are for a regression that also includes wages, mechanical skill, and market access. It can be seen that none of these variables adds any noticeable explanatory power.

TABLE 2
Other Explanatory Variables for Textile Employment: Semiparametric Spatial Regressions

	Dependent Variable: Share of Men Employed in Textiles	
	1831	1851
Literacy, c. 1800	−1.671 (1.937)	−.140 (1.580)
County banks, 1796	−.064 (.431)	−.342 (.368)
Lawyers, 1730	.016 (.444)	−.378 (.386)
Booksellers, 1761	.023 (.358)	.155 (.294)
Adjusted R^2	.649	.652
AIC	137.6	114.1
S(lon, lat)	.682	.709

Note.—Semiparametric spatial regressions. Dependent variable is the employment share of textiles among all males over 20 in 1831 and among males aged 20–29 in 1851. Standard errors are in parentheses. The approximate significance of the thin-plate spline is given by S(lon, lat). Regressions include skill, wages, market potential, and county dummies from first columns of table 1. "Literacy" is the percentage of convicts who were literate. "Density" is the density of 1700 population relative to county farmland. "County banks" is the number of country banks, "Booksellers" the number of booksellers, and "Lawyers" the number of attorneys, all per capita. AIC = Akaike information criterion.

C. Instrumental Variable (IV) Results

The natural concern with these OLS results showing how skill supply is strongly correlated with textile employment is that the supply of skills was endogenous: new industries, even as early as the 1790s, may have encouraged inward migration of skilled workers or caused men in traditional industries, such as millwrights and blacksmiths, to become specialized machine builders. To address this concern, as well as the possibility that our skills variable is mismeasured, we employ an IV strategy where we instrument the measure of skills derived from old skilled workers in the 1851 census.

Our instrument for skill supply is the median fee charged to become an apprentice watchmaker between 1750 and 1779, taken from the records of the Watchmakers' Company assembled by Moore (2003). The justification for this instrument is that there would appear to be no direct path linking the cost of becoming a watchmaker in the mid-eighteenth century with the number of mostly unskilled factory hands in textile mills over half a century later.

At the same time, we would expect these fees to be a strong proxy for the supply of mechanical skill on the eve of the Industrial Revolution. As Ben Zeev, Mokyr, and van der Beek (2017) show, similar trades demanded similar fees, so we can be quite confident that counties that had a larger supply of masters making things like locks, guns, and instruments would charge lower fees in the market for apprenticeship. The close relationship between mid-eighteenth-century apprenticeship fees and the number of skilled workers trained in each county around 1800 is apparent in figure 5.

The determinants of skill supply are analyzed in table 3. The table indicates that the share of mechanics in 1851 was strongly predicted by apprenticeship fees, proximity to coal, and population density relative to farmland in 1700, an indicator of the presence of protoindustry. Land quality, measured by average land tax per acre in 1700, had a smaller impact. It might be argued that low apprenticeships fees are simply a proxy for low wages, but, as the final column shows, the results are little changed if the ratio of apprenticeship fees to wages is used.

Results for the IV regressions are given in table 4 for textile employment in 1831 and 1851, alongside OLS and semiparametric estimates. The IV standard errors are somewhat larger, but, as the Wu-Hausman test indicates, the coefficient estimates change little after instrumenting, suggesting that the tighter OLS confidence intervals would seem to be appropriate.

VI. Regression Results: Metallurgy

The indispensable role of coal in early British industrialization beyond being a source of heat, we have argued, is in the array of metalworking

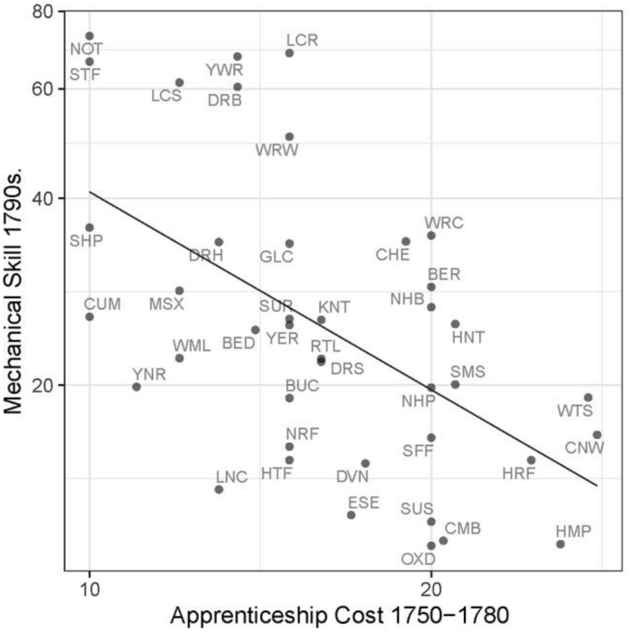

FIG. 5.—Apprenticeship fees for watchmaking 1750–80, and the supply of mechanical skill in the 1790s; logarithmic axes. Full county names corresponding to these abbreviations can be found in the replication files.

skills—ranging from blacksmith work and iron smelting to casting watch springs and pinions—that it allowed to accumulate. Here we examine three heavy-metalworking classifications: metal manufacturing, metal products, and sheet metal. Whereas the 1831 categories for textile employment are systematic, those for metalworking activities are chaotic, reflecting the novelty of many of these activities, so we restrict ourselves to the 1851 data.

The relationship between aggregate employment in metal industries and coal distance is shown in figure 6. Naturally, the relationship with coal proximity is strong, but what is equally important, and again somewhat disguised by the logarithmic axes, is the concentration of the industry in three neighboring counties in the West Midlands—Staffordshire, Warwickshire (which includes Birmingham), and Worcestershire—and to a lesser extent in West Yorkshire, around Sheffield, where suitable coal had made them centers of metalworking skill since at least the seventeenth century.

Table 5 shows regression results for these three activities. It can be seen that for all three activities, market potential paired to being in the traditional centers of the West Midlands is a strong predictor, especially for metal manufacturing. After these are controlled for, proximity to coal (with or without a quadratic term) has no explanatory power. For randomized standard

TABLE 3
FACTORS AFFECTING THE SUPPLY OF MECHANICAL SKILL: SEMIPARAMETRIC SPATIAL REGRESSIONS

	Dependent Variable: Share of Mechanics in 1851			
Apprentice fee	−.570	−.491	−.531	
	(.239)	(.164)	(.133)	
Apprentice fee/wage				−.475
				(.138)
Land tax, 1707		−.085	−.080	−.083
		(.141)	(.115)	(.120)
Population density, 1700		.818	.552	.533
		(.144)	(.133)	(.139)
Distance to coal			−.596	−.603
			(.140)	(.147)
Adjusted R^2	.533	.841	.898	.888
AIC	30.0	−13.0	−31.8	−27.7
S(lon, lat)	.105	.004	.003	.005

NOTE.—Dependent variable is the share of males aged 60–69 listed as mechanics in 1851, by county of birth. Semiparametric spatial regressions: S(lon, lat) gives approximate significance level of a thin-plate spline in longitude and latitude. Standard errors are in parentheses. Regressions including population density include a dummy for London. All other variables are in logs. AIC = Akaike information criterion.

errors, the significance of location for the first three activities was so strong that they were unmatched in any simulation, so the heteroskedasticity-robust values are reported instead. The mechanical skill variable adds no explanatory power, except for metal products. Despite their importance to the

TABLE 4
TEXTILE EMPLOYMENT IN 1831 AND 1851: SEMIPARAMETRIC, OLS, AND IV

	Share of Men Employed in Textiles					
	1831			1851		
	SP	OLS	IV	SP	OLS	IV
Skills, 1790s	2.022	2.125	3.178	1.151	1.703	2.466
	(.503)	(.459)	(1.422)	(.398)	(.332)	(1.119)
Wage, 1760s	−4.776	−6.960	−5.169	−3.035	−4.908	−3.686
	(2.742)	(1.599)	(2.634)	(2.109)	(1.136)	(2.026)
Market potential, 1750	.712	.713	.484	.503	.499	.340
	(.301)	(.228)	(.481)	(.217)	(.188)	(.392)
Adjusted R^2	.684	.655	.606	.813	.613	.567
Wu-Hausman	. . .	. . .	.286	. . .	. . .	.388
Weak instruments	. . .	. . .	.007	. . .	. . .	.015
S(lon, lat)	.641	. . .	. . .	.070	. . .	. . .

NOTE.—Dependent variable is the employment share of textiles among all males over 20 in 1831 and among males aged 20–29 in 1851. Apprentice fees are used as the instrument for mechanical skills. "SP" denotes spatial semiparametric regressions. Heteroskedasticity-robust standard errors are in parentheses. Regressions include longitude and latitude and a dummy in 1831 for Shropshire and in 1851 for Staffordshire. All other variables are in logs. "Wu-Hausman" and "Weak instruments" report the significance levels of tests for differences in OLS and IV coefficients and for weak instruments, respectively.

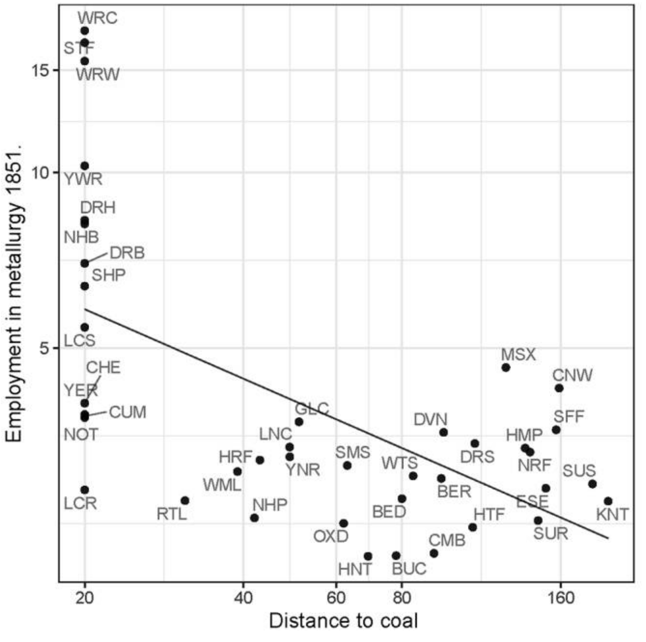

FIG. 6.—Distance to coal and employment in metallurgy 1851; logarithmic axes. It can be seen that proximity to coal was a necessary but not sufficient condition for a large industry: the three West Midlands counties around Birmingham (Stafford [STF], Warwick [WRW], and Worcester [WRC]), and West Yorkshire around Sheffield had been accumulating skill in metalworking since at least the sixteenth century. Full county names corresponding to these abbreviations can be found in the replication files.

modern sector, the metallurgical industries, even as late as 1851, still depended heavily on traditional skills in forging and smelting, and the mechanical aptitude that was required in the construction and maintenance of textile machinery was less important for the location of this industry; different skills mattered.[21]

The importance of metalworking skills was recognized early on by James Watt. In a letter to one of the founders of the Carron Ironworks in 1765, he wrote that "you ask what is the principal hindrance to erecting engines? It is always smith-work." Watt found the skills he needed in Birmingham, where business partner Matthew Boulton had promised him artisans who could work "with as great a difference of accuracy as there is between the blacksmith and the mathematical instrument maker." In the words of the statesman Richard Cobden, "Our strength, wealth, and commerce grow out of

[21] The other new industry reliant on coal for heat in the eighteenth century was pottery, but it was overwhelmingly concentrated in Staffordshire, which was a major center for centuries before Josiah Wedgwood pioneered the mass production of quality tableware.

TABLE 5
DETERMINANTS OF EMPLOYMENT IN METALLURGY IN 1851

	Dependent Variable: Employment in Metallurgy, 1851			
	Total	Metal Manufacturing	Metal Products	Sheet Metal
Traditional metal area	1.197	1.966	1.114	.864
	(.159)	(.411)	(.145)	(.283)
Distance to coal	−.145	−.185	.039	−.244
	(.166)	(.293)	(.121)	(.299)
Market potential, 1750	.139	.558	.097	.383
	(.065)	(.188)	(.059)	(.114)
Skills, 1790s	.314	.444	.323	.138
	(.144)	(.359)	(.128)	(.257)
Adjusted R^2	.874	.756	.819	.670
AIC	−4.8	78.5	−6.4	40.8
S(lon, lat)	.071	.056	.077	.218

NOTE.—Dependent variable is the share of males aged 20–29 employed in metallurgy. Standard errors are in parentheses. Semiparametric regressions: S(lon, lat) is the approximate significance of a thin-plate spline term in longitude and latitude. "Traditional metal area" is a dummy for three West Midland counties: Staffordshire, Warwickshire, and Worcestershire. "Metal manufacturing" contains a dummy for Rutland. All other variables are in logs. AIC = Akaike information criterion.

the skilled labour of the men working in metals. They are at the foundation of our manufacturing greatness."[22]

VII. Regression Results: Traditional Industry

Having discussed textiles and metallurgy, the two sectors almost synonymous with the Industrial Revolution, as a falsification test we consider how well the factors we have emphasized explain the location of traditional manufacturing activities: in other words, can they appear to explain employment in sectors that they should not be able to explain? The variables we stress here (mechanical skills and low wages for textiles and a tradition of using coal as a source of thermal energy for metallurgy) explain modern industry, but, as table 6 shows, they do not correlate systematically with traditional manufacturing sectors whose technology was relatively static during our period. Table 6 shows that for the major traditional sectors of food, garments, shoes, and woodworking, wages are the only important variable for food and garments, and skills have no explanatory power.

VIII. Conclusions

Mechanical and related skills, then, were crucial to the success of the Industrial Revolution. Britain's advantage on other European nations in this

[22] The quotations are from Smiles (1863, 140), Smiles (1865, 203), and Smiles (1863, 331).

TABLE 6
EMPLOYMENT SHARES OF TRADITIONAL INDUSTRIES IN 1851: SEMIPARAMETRIC SPATIAL REGRESSIONS

	Dependent Variable: Share of Men Employed in Traditional Industries, 1851			
	Food	Garments	Shoes	Wood
Skills, 1790s	−.042	.154	.025	.028
	(.054)	(.112)	(.084)	(.152)
Wage, 1760s	−.600	−.652	−.523	.290
	(.314)	(.654)	(.498)	(.885)
Market potential, 1750	−.010	−.021	.028	−.116
	(.034)	(.070)	(.051)	(.095)
Adjusted R^2	.476	.372	.728	.017
AIC	−48.1	11.9	−23.0	36.4
S(lon,lat)	.000	.312	.692	.780

NOTE.—Dependent variable is the employment share of males aged 20–29 in 1851. Semiparametric spatial regressions: S(lon, lat) gives the approximate significance level of a thin-plate spline in longitude and latitude. Standard errors are in parentheses. Regressions include a dummy for London, and "Shoes" includes one for Northamptonshire. All other variables are in logs. AIC = Akaike information criterion.

respect explains why it was the technological leader of Europe for over a century. The question why this was so has a number of components. First and foremost, as already noted, regional specialization due to market integration stimulated the demand for artisan skills in the regions specializing in those products. Second, the apprenticeship system in Britain was more flexible and market oriented than elsewhere, and the institutional structure that enforced the institution was more effective (Mokyr 2019, 2021). Third, the lower inequality of income distribution in Britain in the first half of the eighteenth century meant that there was considerable demand for middle-class luxuries that demanded high levels of skills. Finally, as argued in Kelly, Mokyr, and Ó Gráda (2014), the average quality of the entire British labor force was higher than that on the Continent.

If we assume, with some simplification, that the quality of mechanical competence can be summarized in a single variable that is distributed symmetrically over the labor force, it is a characteristic of symmetrical distributions that fairly small differences in the means of two populations are amplified to much larger differences in the density of the respective upper tails. Hence, the very top artisans of Britain, what has been termed upper-tail human capital, had considerably more mass than their continental neighbors, providing Britain with a serious advantage in an age when such artisans and their tacit knowledge of mechanical skills may have mattered more than either before or after.

For a generation now, the debate on the origins of the Industrial Revolution itself has been overshadowed by the realization that its macroeconomic impact was at first modest, reflecting the fact that the sectors that grew fastest had started out small (Crafts and Harley 1992). From this spread a widespread belief that the Industrial Revolution was less of an epochal change in human history than a narrow event confined to a few sectors, such as cotton, iron, and steam, in an economy that was otherwise fairly static.[23]

Although our empirical analysis here has centered on textiles and iron, this narrow view of the Industrial Revolution has increasingly been recognized as untenable. First, Broadberry et al. (2015) have demonstrated that slow but persistent output growth across a broad range of industrial sectors was already under way by the late seventeenth century. Second, technological change is increasingly seen as sustained improvements, most of them anonymous and incremental, across many important activities—as varied as watchmaking, shipping, ceramics, glassmaking, brewing, road transport, paper making, candlemaking, gas lighting, water power, and machine tools—in many cases starting in the early eighteenth century.

Appendix A

Spatial Standard Errors and Semiparametric Regressions

In this appendix, we first show how current spatial standard error corrections tend to return such widely differing estimates as to be of limited utility in practice and then introduce a simple way to estimate accurate results by using a semiparametric regression that includes a spatial spline.

A1. Standard Error Corrections

Regressions with spatial data frequently generate spuriously large t-statistics, for two reasons. First, geographical variables often show strong directional trends (e.g., per capita income rises as one moves away from the equator). Second, because observations tend to resemble their neighbors, effective sample sizes are smaller than they appear, leading to underestimated standard errors.

Starting with the kernel adjustment of Conley (1999), several standard error corrections have been proposed, including the large-cluster methods of Ibragimov and Müller (2010), Bester et al. (2016), and Canay, Romano, and Shaikh (2017) and the principal components approach of Müller and Watson (2021). However, all of these adjustments require the user to set, more or less arbitrarily, the value of a tuning parameter value (the correlation range, the number of clusters, or the average correlation between points), and as table A1 shows, the estimates can be extremely sensitive to small changes in these assumed parameters.

[23] For early dissenting views, see Berg and Hudson (1992) and Temin (1997).

TABLE A1
SIGNIFICANCE LEVELS OF THE MAIN EXPLANATORY VARIABLE IN THREE REGRESSIONS USING DIFFERENT STANDARD ERROR CORRECTIONS

			CONLEY		BCH		CRS		IM		MW	
DEGREE	ROBUST	CLUSTERED	50(0) km	100(0) km	4	6	8	12	8	12	.01	.05
					Africa ($N = 379$)							
0	.000	.001	.000	.000	.084	.032	.031	.020	.174	.300	.005	.046
1	.000	.002	.000	.000	.084	.032	.125	.964	.103	.415	.004	.043
2	.000	.006	.001	.001	.168	.058	.352	.963	.256	.465	.013	.103
					Germany ($N = 324$)							
0	.008	.054	.014	.034	.185	.095	.508	.613	.486	.620	.103	.109
1	.014	.047	.018	.050	.304	.108	.805	.127	.808	.178	.106	.167
2	.009	.041	.015	.055	.287	.179	.961	.340	.943	.275	.128	.228
					Global ($N = 114$)							
0	.000	.032	.000	.001	.319	.190	.016	.999	.273	.717	.059	.288
1	.005	.037	.004	.006	.259	.139	.211	.692	.300	.735	.022	.123
2	.007	.001	.006	.010	.122	.068	.805	.834	.526	.952	.042	.065

NOTE.—In each case, significance levels from .01 upward may be obtained by an appropriate choice of correction and assumed tuning parameter, along with the degree of the included polynomial in longitude and latitude. Significance levels for different standard error corrections. "Degree" presents the polynomial degree of longitude and latitude variables added to each regression: no variables, linear, and quadratic. "Robust" denotes heteroskedasticity-robust standard errors. "Cluster" gives clustered standard errors when the observations were divided into 20 groups of nearest neighbors by *k*-means clustering. "Conley" denotes Conley (1999) standard errors with a Bartlett kernel and cutoff distances of 50 and 100 km for the German data and 500 and 1,000 km otherwise. "BCH" (Bester, Conley, and Hansen 2011), "CRS" (Canay, Romano, and Shaikh 2017), and "IM" (Ibragimov and Müller 2010) are based on large clusters, again chosen by *k*-means clustering, with the assumed number of clusters given below each. "MW" gives Müller and Watson (2021) values, assuming average correlation values between residuals of 0.01 and 0.05.

The table gives the significance level of the main explanatory variable in regressions from three historical persistence studies for Africa, Germany, and countries around the world (Alsan 2015, Voigtländer and Voth 2012, and Alesina, Giuliano, and Nunn 2013, respectively). Successive rows contain increasing polynomials in longitude and absolute latitude, varying in degree from zero to quadratic. It is immediately evident that almost any significance level from .01 and higher may be obtained by an appropriate choice of estimator, assumed parameter, and polynomial in longitude and latitude.

A2. *Semiparametric Spatial Regressions*

The approach that we propose here is to view spatial structure, both trends and local correlation, as an issue not of standard errors but of specification. The standard approach with spatial data is to run a regression of the form

$$y_i = X_i\beta + \eta_i \tag{A1}$$

for observations at geographical sites $i = 1, \ldots, n$, where $\eta \sim N(0, \Sigma)$, and then to attempt to adjust standard errors for spatial correlation. However, leaving standard errors aside, the coefficient estimates $\hat{\beta}$ will be unbiased only if equation (A1) is correctly specified.

In general however, any spatial regression will omit many factors, each of which has a directional trend and local correlation, so a less restrictive specification is

$$y_i = g(\mathbf{s}_i) + X_i\beta + \epsilon_i, \tag{A2}$$

where $\epsilon \sim N(0, \sigma^2 I)$ and g is some unknown function of $\mathbf{s}_i = (s_1, s_2)$, the longitude and latitude of the observations, that reflects the impact of the omitted, spatially correlated explanatory variables. This semiparametric approach allows the spatial structure of the regression to be separated out as a nuisance variable when estimating the coefficients of interest β.

Suppose initially that $y_i = g(\mathbf{s}_i) + \epsilon_i$. Thin-plate spline smoothing estimates g by finding the function $\hat{f}$ that minimizes $\| \mathbf{y} - f(\mathbf{s}) \|^2 + \lambda J(f)$, where $J(f)$ is a function that penalizes overfitting, measured by changes in slope, and λ is a smoothing parameter that controls the trade-off between data fitting and the smoothness of f. Specifically, the thin-plate spline $\hat{f}$ is the solution to the constrained minimization problem

$$\min_f \left\{ \sum_i (y_i - f(\mathbf{s}_i))^2 + \lambda \int \left(\frac{\partial^2 f(\mathbf{s})}{\partial s_1^2}\right)^2 + 2\left(\frac{\partial^2 f(\mathbf{s})}{\partial s_1 \partial s_2}\right)^2 + \left(\frac{\partial^2 f(\mathbf{s})}{\partial s_2^2}\right)^2 \mathrm{d}\mathbf{s} \right\}. \tag{A3}$$

The equation of $\hat{f}$ is given in Wood (2017, 216). The optimal value of the roughness penalty λ is chosen by a generalized cross-validation.[24]

A potential issue with estimating β from equation (A2) is that explanatory variables may have a spatial structure of their own, leading to confounding of spatial effects. Suppose, for concreteness, that there is a single explanatory variable x, so $y_i = \beta x_i + g(\mathbf{s}_i) + \epsilon_i$, and that $x_i = h(\mathbf{s}_i) + \nu_i$. Chen and Shiau (1991), extended to two dimensions by Dupont, Wood, and Augustin (2022), show that β can be estimated consistently by a two-step procedure that substitutes the estimated residuals $\hat{\nu}$ from the second equation for x in the first equation.

To illustrate the reliability of this semiparametric procedure compared with standard error corrections and polynomials in latitude and longitude, we run Monte Carlo simulations on three sets of geographical coordinates: the first is the 41 English counties, the second is a random sample of 150 locations of African ethnic groups, and the third is a sample of 100 German counties from the persistence studies cited above. Coordinates were rescaled so that points lie on a unit square.

We simulate normal variables with mean zero and covariance between sites s_i and s_j at distance h equal to $\Sigma(\mathbf{s}_i, \mathbf{s}_j) = \rho \exp(-h/\theta) + \sigma^2 \mathbf{1}_{ij}$, where $\mathbf{1}_{ij} = 1$ when $i = j$ and zero otherwise. The parameter ρ gives systematic correlation, while σ^2 represents idiosyncratic noise. The range parameter θ controls how fast correlation

[24] The procedure extends to having multiple splines for explanatory variables and to a wide family of non-Gaussian regressions, including binomial, multinomial, and count data. These regressions are straightforwardly estimated with Wood's R package mgcv.

decays with distance: correlation falls to about 0.1 at distance 2θ (Gneiting and Guttorp 2010). In the simulations here, we suppose a fairly strong and empirically realistic spatial structure where $\theta = 0.1$, $\rho = 0.9$, and $\sigma^2 = 0.1$. In simulations where a spatial trend was added to each variable, it took the form of two peaks on a northwest-southeast diagonal used by Wood (2003).

Each entry in table A2 gives the fraction of simulations where a 95% confidence interval contained the true coefficient value of zero. Robust least squares and Conley (1999) standard errors with a cutoff of 0.1 were added for comparison. Successive rows give results when no longitude and latitude terms were added to the regression and then when they were included linearly and quadratically.

Starting with the set of 41 counties, both OLS and Conley perform well in the absence of spatial trends, but their coverage falls to around 0.7 when a trend is added to the variables. For African and German coordinates without trends, they give coverage of 70%–80%, and this falls to 40%–60% when trends are added, even though directional polynomials have been added to reduce spatial structure.

Turning to semiparametric estimates, both uncorrected and two-step estimates perform almost perfectly in the absence of trends. When a trend is added, both continue to perform well, except in the case of England, where the uncorrected regressions have a coverage of only 85% but two-step regressions again have close to nominal coverage.

TABLE A2
Monte Carlo Estimates of 95% Coverage Probabilities for Semiparametric Regressions and Standard Error Corrections over Three Sets of Geographical Coordinates

	No Trend				Trend			
Degree	SP	SP2	OLS	Conley	SP	SP2	OLS	Conley
				England				
0	.93	.93	.91	.88	.85	.93	.70	.66
1	.93	.93	.92	.88	.85	.93	.74	.67
2	.93	.93	.93	.89	.85	.93	.73	.65
				Africa				
0	.91	.93	.64	.82	.90	.93	.41	.58
1	.91	.93	.68	.81	.90	.93	.41	.56
2	.91	.93	.72	.79	.90	.93	.45	.55
				Germany				
0	.92	.94	.74	.82	.93	.94	.43	.57
1	.92	.94	.78	.82	.93	.94	.49	.57
2	.92	.94	.80	.81	.93	.94	.48	.54

Note.—Proportion of 95% confidence intervals containing the true coefficient of zero. Simulations are based on the coordinates of 41 English counties, 150 African tribal areas, and 100 German counties, where the variables do or do not contain spatial trends. “SP” denotes a semiparametric regression with a thin-plate spline in latitude and longitude; “SP2” uses a two- step procedure for potential spatial confounding; “OLS” denotes ordinary least squares with robust standard errors; “Conley” uses a Conley kernel correction. “Degree” presents the polynomial degree of longitude and latitude variables added to each regression: no variables, linear, and quadratic.

Appendix B

Transportation

By 1760, England already had 1,400 miles of navigable rivers connecting places like Manchester and Sheffield to the sea, and by 1830 it had added a further 2,600 miles of canals (Satchell 2017). Between 1750 and 1770, 10,000 miles of road were turnpiked, increasing to 20,000 miles by 1830; and Bogart (2005) estimates that between 1750 and 1820, road freight charges fell by around 40%. Furthermore, Britain had no internal tariffs, unlike fragmented Italy and Germany and even seemingly unified ancien régime France and Spain.

Between 1760 and 1783, the tonnage of ships moving bulk goods around the coasts rose from 155,000 to 270,000 tons, and by 1824, now including Scotland and Ireland, this had risen to 833,000 tons. The average annual shipment of coal from the northeast to London has been estimated at half-a-million tons a year in the first half of the eighteenth century and had risen to 1.5 million tons by 1780, reaching 5.7 million by 1829; and on the eve of the Industrial Revolution, there were no fewer than 580 locations in England and Wales that were accessible to coal shipments by water (Armstrong and Bagwell 1983, tables 15, 19–22; Hausman 1987, table 2; Szostak 1991).

Appendix C

Data Sources and Construction

Measures of skill of men aged 60 and over born in each county or resident in each county are taken from the 1851 census in the UK Data Archive (http://icem-nesstar.data-archive.ac.uk/webview/). Workers are assigned by HISCO (historical international classification of occupations) code as follows: blacksmiths, 83120–83150; toolmakers, 83210–83400; gunsmiths and locksmiths, 83210–83700; mechanics, 84110, 84130–84190; millwrights, 84120; watch and instrument makers, 84220–84290; and sheet-metal workers, 87330–87390.[25] These are expressed per 100,000 men over 60 who were working, retired, or unemployed.

Textile employment in 1831 is from Marshall (1833, 10–11). Apprenticeship fees for the London Watchmakers Company are from Moore (2003).

Wages of agricultural laborers for the 1760s and 1833 are taken from Hunt (1986, with the entry for Nottingham corrected to match the original source) and population data from Wrigley (2009).

Water flow for each square kilometer of England is based on the area that drains into it, multiplied by the tangent of its slope, both from the US Geological Survey HYDRO1k database. Each county is assigned a value equal to the 98th percentile of the flow across its squares. Coal distance is the distance of the center of each county to the nearest county with a coal field. Counties with a coalfield were assigned a distance of 20 km.

Literacy is the percentage of male convicts from each county around 1800 who were literate, from Nicholas and Nicholas (1992, table 3), and height is the height of army volunteers from 1788 to 1805, from Floud (1986).

[25] See http://historyofwork.iisg.nl/major.php for details of HISCO codes.

Market potential is the sum of aggregate income (1760s wage times 1750 population) of each county, weighted by the inverse squared distance to the center of the county. "Booksellers" is the number of booksellers in 1751, measured by Dowey (2016), relative to county population in 1750. "Lawyers" is the number of attorneys in 1730 relative to county population, from Aylett (1987), and the number of country banks in 1796 is from Brunt (2006).

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