Fighting for Growth: Labor Scarcity and Technological Progress During the British Industrial Revolution*

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Abstract

New data and evidence demonstrate a link between labor scarcity and the adoption of labor-saving technology in industrializing England. During the Napoleonic Wars, up to 10-14% of the male population served in the armed forces. Where recruitment was heavy, more machines economizing on labor were adopted. Naval recruitment, instrumented by warships' coastal access, provides exogenous shocks to labor scarcity. These shocks led to the adoption of labor-saving machines, but not non-labor-saving technologies. Importantly, there is a synergy between skill abundance and labor scarcity – where labor shortages boosted machine adoption, technology afterwards improved more rapidly.

Keywords: Technology adoption, learning-by-doing, Industrial Revolution.

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Before the Industrial Revolution, output per capita and living standards stagnated for millennia – Malthusian forces regularly nullified the gains from technological progress (Galor, 2005). From the middle of the 18th century onwards, growth and technological change accelerated in Britain – slowly at first and then rapidly, eventually outpacing population growth. Understanding the accelerating pace of technological change is central to any wider explanation of the Industrial Revolution (Jones, 2001). Today, two main interpretations exist. According to Allen (2009), the "Industrial Revolution was invented in Britain in the eighteenth century because that was where it paid to invent it", driven by cheap energy and high labor costs. In this perspective, the British Industrial Revolution is an example of directed technological change, in the tradition of Hicks (1932), Habakkuk (1962), or Acemoglu (2007). In contrast, Mokyr (2009) emphasizes human capital and cultural factors such as the Enlightenment – the need to combine open discourse and scientific inquiry with practical know-how in the hands of "tinkerers." Britain, according to this view, was uniquely blessed by an abundance of savants and skilled mechanics:[1] Industrialization began in places with more skilled craftsmen (Kelly et al., 2022), not higher wages.

Examining the causal role of factor scarcity in the transition to self-sustaining growth is challenging. Credible analysis requires cross-sectional variation in labor scarcity. Such variation should be exogenously assigned, and not simply reflect local economic conditions. Detailed data on skill availability and the cost of labor are scarce, as is information on the adoption of new technologies. It therefore remains an open question whether labor shortages facilitated the transition to self-sustaining growth (Crafts, 2011).[2]

In this paper, we examine the determinants of technological progress during the British Industrial Revolution, offering a unified perspective that assigns a role to both labor scarcity and human capital. To measure technological change, we collect new, granular data on the diffusion of technologies (both labor-saving and not)

[1]This is in line with models of directed technological change if labor and technology are complementary (Acemoglu, 2007).

[2]Recent progress includes evidence from the cross-section of 41 English counties, documenting an association of industrial activity with low wages and skill abundance (Kelly et al., 2022).

in England. We focus on technology adoption, not invention, since productivity growth ultimately depends on usage. Our setting involves a large shock to labor markets: The French Revolutionary and Napoleonic Wars (1793-1815) saw a rapid expansion of Britain's armed forces, leading to significant labor market imbalances. These shifted local sex ratios decisively in favor of women. Labor-saving machines were adopted faster where the navy and the army recruited more men.[3] Military recruitment went hand-in-hand with the adoption of labor-saving technology – but the same was not true of non-labor saving technology.

Our paper is the first to demonstrate a large, causal effect of labor shortages on the adoption of *labor-saving* technologies during the British Industrial Revolution. We present results using both army and naval recruitment, but focus on naval recruitment for identification. Contemporary accounts noted that coastal districts often saw both heavy recruitment by the Royal Navy and rapid adoption of labor-saving machinery. Recruitment was heavily decentralized. It was often carried out by press-gangs which compelled individuals to serve involuntarily (Rodger, 2006).[4] In coastal areas, what mattered for recruitment intensity was proximity to suitable anchorage. We thus instrument the number of men on navy ships taken from any one location by the distance from the nearest coast to locations suitable for use by the large ships that did the most recruitment. Within the set of coastal locations, places closer to the nearest anchoring spot usable by large warships saw heavier recruitment and faster adoption of labor-saving machinery.[5]

We also document an important role for human capital: labor shortages and ample local skill supply combined to further increase technology adoption and the rate of productivity improvement, along the lines of recent work by Kelly et al. (2022). A combination of labor shortages and mechanical skills facilitated technological progress. We use data on apprenticeship contracts to measure local skill

[3]Importantly, we directly observe variation in the quantity of labor across local labor markets. While the mechanism at work depends on the relative price of labor, price data alone is harder to interpret (Acemoglu and Finkelstein, 2008) and far more scarce.

[4]Some recruiting was centralized via the Impress Service; but during periods of strong needs to find men, captain's search parties were an important additional source of men (Dancy, 2018).

[5]The effect is not driven by simple proximity to the coast: for the IV analysis we consider only coastal areas and always control for direct distance to the coast.

supply. In locations where young men trained as blacksmiths, watchmakers, and millwrights, labor shortages during the Napoleonic Wars translated into rapid technology adoption. The same pattern is visible for technology improvements — in locations with many local craftsmen, military recruitment led to more participation in Royal Agricultural Society of England (RASE) competitions. Far from being mutually exclusive interpretations of the British Industrial Revolution, our findings suggest that both the Mokyr (2009) and Allen (2009) theses have explanatory power – and both factors, labor shortages and local human capital, interacted to facilitate technology adoption.

We use three newly-collected datasets. First, we compile a comprehensive individual-level database of naval and army recruitment in England during the Napoleonic Wars. At their peak the army and navy had an estimated 350,000 men under arms. The British Army recruited across the country, and especially so in areas from which traditional regiments were drawn (Kirby and Komlos, 1994). The Royal Navy grew from 16,000 men in 1792 to nearly ten times that number in 1812. We hand-collected a sample of ships' muster-rolls – personnel records of individual ships – and digitize information on the geographical origin of recruits. These data allow us to measure shocks to the labour market due to naval recruitment.

Our second new dataset measures the adoption of both labor-saving and non-labor saving technologies at the same highly-disaggregated level. We use granular data on the adoption of ten technologies over the period 1790-1830 in over 10,000 English parishes, using information from historical newspapers. Based on detailed agricultural manuals, we classify machines into labor-saving and non-labor saving technologies: Labor-saving machines replaced manual work; non-labor saving machines facilitated work previously not done at all.

The third dataset records the number and quality of experimental agricultural machines, presented at meetings of the Royal Agricultural Society of England (RASE). The society organized competitions across England after its founding in 1838, awarding prizes to the best designs. We show that areas with more military recruitment saw more adoption *and* more inventive activity, as measured by the number of competitors in RASE events. Machines were also more productive in areas where more competitors entered, suggesting that the (temporary, but long-lasting) shock to labor supply during the Napoleonic Wars had far-reaching consequences.

Our results are robust to a wide range of alternative approaches. Discrete choice models to explain the extensive margin of adoption yield similar or stronger results, and the size and significance of our effects is not undermined when we correct for potential correlation of spatial errors. We also show that the effect of naval recruitment on technology adoption does not reflect exposure to commercial port activity, or to a more active land market. Finally, we examine whether possible limitations of our main source for adoption – newspapers – might be driving results, and find no evidence for this notion.

By linking the adoption of labor saving technology to labor scarcity, our findings provide empirical support to theories of directed technical change (Hicks, 1932; Habakkuk, 1962; Acemoglu, 2002, 2003, and, 2007). These models clarify under what conditions labor scarcity promotes innovation, and highlight the importance of technologies' factor bias: only (strongly) labor saving technologies benefit from labor scarcity. Several papers provide support to this prediction: Hanlon (2015) shows how during the US Civil War UK inventors responded to the drop in US cotton imports by introducing more machines designed for non-US cotton yarns. Similarly, Andersson et al. (2022) and San (2022) exploit different exogenous shocks to labor supply to show that higher wages can lead to more labor saving innovation.

A closely related set of papers examines technology adoption, showing how wages affect automation in the US health sector (Acemoglu and Finkelstein, 2008), across US manufactures (Lewis, 2011) and across countries, US cities and US industries (Acemoglu and Restrepo, 2020).[6] For the case of 19$^{\text{th}}$ century France, Franck (2022) finds ambiguous effects of labor shortages on technology adoption. Relatedly, higher wages can promote capital/labor substitution (Hornbeck and Naidu, 2014; Clemens et al., 2018; Abramitzky et al., 2022; and Andersson et al., 2022). Because new capital often does not embody new technology, these papers provide only limited

[6] Another literature examines the consequence of new technology. Autor et al. (2003) showed that IT technologies reduced demand for routine tasks and increased them for skilled labor. Acemoglu and Restrepo (2018) investigate the impact of automation on labor demand.

evidence on directed technological change.[7]

Our paper also contributes to the long-standing debate on the origins of the British Industrial Revolution. Economic historians have recognized several factors that made 17th and 18th century Britain special, including institutions (North and Weingast, 1989), overseas colonies (Inikori, 2002), culture and psychology (McCloskey, 2010), slave wealth (Heblich et al., 2022), natural resources (Wrigley, 2010), geography, or chance (Crafts, 1985). While literacy rates were low (Mitch, 2004), Britain had an unusually large number of highly skilled mechanics: workers who had acquired significant non-codifiable knowledge through on-the-job training (apprenticeships) and were able to introduce a constant stream of micro-inventions and improvements to machines (Kelly et al., 2022).

Relative to the existing literature, we make three main contributions. We are the first to provide well-identified evidence of labor scarcity driving technological progress during the British Industrial Revolution. Second, by documenting the effect of labor scarcity on technology adoption in agriculture, we show that the mechanism hypothesized by Allen (2009) applies outside the textile and metal sectors. Moreover, by focusing on quantities of labor (and not wages), we can measure factor scarcity directly. In combination, our cross-sectional evidence allows us to test Allen's theory and show its relevance beyond the (relatively small) number of "leading sectors" of the Industrial Revolution. Our third main contribution is to demonstrate a synergy between labor scarcity and skill abundance. Where labor scarcity coincided with the presence of local trained mechanics, technology adoption accelerated – and so did the productivity of new machines. This suggests a unified interpretation of the British Industrial Revolution, with a role for continuous military conflict inducing factor scarcity as well as human capital.

[7] In areas of labor scarcity, employers can either use new technology (moving to a different isoquant) or more of the existing technology (a different point on the same isoquant). Testing theories of directed technological change requires detailed data on the technologies in use.

1 Historical Background

At the height of the Napoleonic Wars, in 1812, an official county survey on the state of agriculture in Dorset observed that:

> *A considerable number of thrashing [sic] machines have been erected in this county... the principal inducement for using them is a scarcity of labourers, which, in a state of warfare, may be expected to be felt most in maritime districts.*

In other words, contemporary accounts observed that: a) labor scarcity led to technology adoption, in this case for threshing machines; b) warfare was the key driver of this scarcity; and, c) labor shortages were more pressing in 'maritime' (not simply 'coastal') districts – something that the authors considered a predictable outcome. In this section, we provide context for this mechanism, describing the growth of industry, the state of agriculture and the economic impact of the Napoleonic Wars.

1.1 The First Industrial Nation

Britain had relatively high wages, productivity, and per capita income on the eve of the Industrial Revolution (Allen, 2009), rivaled only by the Netherlands. Wages were particularly high relative to the cost of energy (Allen, 2009). Total real GDP growth during the Industrial Revolution was relatively slow – 1.2% p.a. in the second half of the 18$^{\text{th}}$ century, rising to 1.7 to 2.3 % in the next 50 years. Real per capita income growth was the 0.3-0.9% range, and total factor productivity averaged less than half a percent during the 70 years after 1760 (Broadberry et al., 2015). Nonetheless, to achieve growth in per capita output at all during a period of rapidly expanding population was a major achievement compared to pre-industrial economies, signaling a decisive break away from Malthusian shackles (Wrigley and Schofield, 1981).

Structural change was the most dramatic feature of Britain's industrialization. Almost every country on the eve of industrial take-off had a substantial productivity deficit in agriculture (Crafts, 1985). In contrast, in Britain these shares were equal at 31% as early as 1801 (Broadberry et al., 2015). Britain also "released" surplus labor from agriculture long before other countries (Crafts, 1985). In 1759, industry employed more than a third of the labor force; a century later, almost half of all employment in Britain was in industry, and less than a quarter in agriculture.

1.2 Agriculture and agricultural technology in Britain

British agriculture was highly productive. There were almost no small, inefficient farms (Heldring et al., 2021), and agriculture used capital intensively. Farming was highly commercialized, centered on large tenant farms producing output for the market, in contrast to continental, peasant-based farming (Wrigley, 1985). New methods such as crop rotations, fertilization, and drainage boosted productivity.

Hired labor was key for operating large-scale, efficient farms. They used both agricultural servants on annual contracts, and day laborers (Kussmaul, 1990). During the early modern period, many laborers lost access to the village commons -making them increasingly reliant on wage income (Allen, 1992; Heldring et al., 2022). Britain operated a generous system of income support, the "Poor Law" (Boyer, 1990). Relief was reserved for those with "settlement" in a parish (obtained by birth, marriage, or apprenticeship); to leave was to lose income support, discouraging mobility.

Several new agricultural technologies emerged during the Industrial Revolution. Some of these technologies were labor-saving. Threshing was particularly labor-intensive. It accounted for approximately half of all labor performed on English farms from November to March. The Scottish engineer Andrew Meikle invented the first threshing machine in the late 18th century. Originally powered by horses, they soon used water and then steam power (Caprettini and Voth, 2020). Initially, high costs and low reliability limited adoption to northern England, where agricultural wages were higher (Macdonald, 1975; Caird, 1852).

Over the following years, as war led to labor shortages, the machines started to appear in southern England. Over the next half-century, threshing machines spread widely, eventually replacing hand-threshing. The impact on employment was immediate. The Poor Law Commission surveyed conditions in Britain in 1832. The return from Burnham, Buckinghamshire, illustrates their impact:

> *Q. Has the use of threshing machines ... had any effect upon the wages of labor?*

A. Not the least...

Q. Do your farmers employ fewer hands than they did before those machines were introduced?

A. Considerably. [...]

Q. How soon after their introduction did they begin to employ fewer hands?

A. Directly they began working them; instantly.

Q. How many months will a threshing machine take to thresh out the produce of a farm which before took the men ten months?

Q. They will thresh it out in two months."

The new machines raised productivity fivefold and reduced labor demand (Caprettini and Voth, 2020); they also hit a labor market with many frictions. Despite a massive reduciton in labor demand, wages failed to adjust; wages may therefore be a poor indicator of labor market conditions.

Horse hoes that removed weeds and horse rakes allowed further labor savings: Fussell (1952, p.139) observes that before the horse rake "it needed nearly as many men to make hay as the blades of grass they gathered," and Long (1963) estimates that one horse rake could do the work of 20 men. Rahm (1844, p.254) finds that the horse hoe was invented because the hand hoe was not "sufficiently expeditious on a large scale." Mowers cut the harvest and reapers collected it: these machines replaced some of the most labor intensive agricultural activities (David, 1966). Mowers diffused only after reapers did, and reaper technology was rudimentary for some time (Fussell, 1952). In contrast, turnip cutters, chaffing machines and cake crushers facilitated fodder production: cutting turnips, grinding chaff, and crushing the cake residue of oil manufacture. Before their introduction "there was little feed preparing" and "beasts had to survive as best they could" (Fussell, 1952, p.180). They were adopted because they allowed to produce more fodder from the same produce (Young, 1813); this used additional labor, instead of saving it.

1.3 Britain during the Napoleonic Wars

The wars against revolutionary France and Napoleon lasted from 1793 to 1815, with Britain at war throughout, except for the brief Peace of Amiens (1802-03).

Napoleonic France had conquered most of continental Europe, while the United Kingdom seized most French colonies and those of her allies. The UK relied on a large fleet to support its allies, conduct amphibious landings, cut France and her allies off from her colonies, and blockade trade routes. War was the single most expensive activity an early modern state could engage in, and its cost regularly outstripped revenues from ordinary taxation. Britain financed its wars mostly through borrowing (Brewer, 1988). By 1815, Britain's debt-to-GNP ratio exceeded 200%.

1.4 The British Armed Forces

To fight France, Britain rapidly expanded all branches of her armed forces. In 1792, the Royal Navy had numbered around 16,000 sailors; at its peak in 1812, it had grown tenfold, to around 160,000 men and almost 1,000 ships (Rodger, 2006). The British Army reached a peak of 200,000 men in 1813. After 1815, both branches shrank: by 1821 the navy's size had declined to only 14,000 men, while the army was down to 110,000 (Clowes, 1899; Fortescue, 1899). In combination, the British armed forces counted more than 350,000 men under arms at the moment of greatest expansion (1813). This is equivalent to 10-14% of the adult male labor force in Great Britain at the time (Wrigley and Schofield, 1981): assembling and maintaining such massive armed forces resulted in a major labor market shock.[8]

The terms of service, losses and high turnover exacerbated the pressure of war on the labor market. Combat losses were relatively low, but illness took a substantial toll. Overall British casualties amounted to over 300,000 for the period 1804-1815 – 90,000 for the Royal Navy and 220,000 for the British Army (Dumas and Vedel-Petersen, 1923). In the face of such losses, maintaining armed forces equivalent to 10-14% of the adult male population required an even higher proportion of all men.

The British Army mainly recruited from the lower classes. Pay was low and conditions were harsh. The Duke of Wellington famously observed: "We have in the service the scum of the earth as common soldiers." Some 43 percent of army recruits were day laborers (Floud et al., 1990). British Army recruitment directly contributed to rural labor shortages.

[8]Britain had a male population of approximately 4.4 million in 1801. Of these, approximately 60% (2.6 million) would have been prime-aged men.

Naval recruitment created additional pressures on the civilian labor market. The navy needed able seamen and sought to recruit merchant sailors. Impressment was common. Navy recruitment was also decentralized: each captain had to man his own ship. Pressing sailors created indirect pressure on the local labor employed in non-seafaring activities. As both the Royal Navy and the merchant marine grew during the wars (Dancy, 2012, reproduced in Figure A.1), naval recruitment heightened labor demand in coastal districts. Our IV strategy exploits determinants of naval recruitment to estimate causal effects.

Recruitment intensity varied from location to location; migration did not offset its effect. Some recruits came from abroad (Dancy, 2018; in our data, 10 percent of recruits are Irish). However, the vast majority of military men came from Britain. As the General Views of Agriculture suggest, war-induced labor shortages were readily apparent to contemporaries.

2 Data

We introduce new data on military recruitment, technology adoption, and the productivity of agricultural machines in 19th century Britain. Each of these sources contain highly granular data for early 19th century England and Wales at the level of around 10,000 parishes, which we aggregate to some 2,600 equally-sized cells. We describe data sources in this section and provide additional details in Appendix A.

2.1 Military recruitment

To trace the impact of military recruitment, we collect enlistment records from the two main branches of the British armed forces – British Army and Royal Navy – using both existing and newly collected data sources.

British Army. Since 1760, the British Army collected records of their recruits in regimental muster rolls. Musters were compiled monthly or quarterly for pay and accounting purposes, and were later collected in regimental volumes by the National Archives. The records report the name of every soldier, along with place of birth, age and several physical characteristics.

We measure the intensity of army recruitment using data originally collected by

Floud et al. (1990), who assembled information on 23,749 soldiers enlisted during the Wars against France (in the 1790s, 1800s and 1810s). Floud and his team harmonized the spellings of soldiers' place of birth; we can geolocate around 64 percent of this sample in either England or Wales (around 15,000 recruits). Floud digitized a random sample of new recruits in every decade: his sampling procedure provides reasonable geographical coverage (Figure 1 – Panel A).

Royal Navy. We create a new database of naval recruitment, based on ships' muster rolls. These accounting records were compiled aboard each Royal Navy ship every two months by the purser.They record each man's name and place of birth, as well as rank and whether they were pressed into service. Some records do not include enough detail to establish the birth place; others refer to overseas locations.

We combine three different samples of ship records. These contain 95,014 sailors on 262 ships commissioned between 1793 and 1815. The samples are sourced from the Battle of Trafalgar project[9] (33 ships and some 18,000 men), Dancy (2018) (134 ships and 42,000 men) and the newly digitized musters (95 ships and 35,000 men) which we collect. Because the ships that fought with Nelson at Trafalgar are larger than the typical Navy ship of the time, small vessels are slightly oversampled in the other two sources. The final list is balanced in terms of size (as proxied by the number of guns) and port of commission. Out of 95,000 individual records, we can assign over 30,000 to a parish in England and Wales. Random selection of ships ensures that our sample is representative of the population of Royal Navy sailors.

Geographical distribution and involuntary recruitment. Panels A and B of Figure 1 summarize the geography of military recruitment in England and Wales, with darker cells experiencing higher recruitment rates. Recruits in both forces were drawn from across England and Wales. We estimate the share of "pressed men" (naval personnel serving involuntarily) as between 51 and 86%.[10] Thus, for at least half of naval recruits, self-selection into service was of minor importance.

[9]See the Battle of Trafalgar project at https://www.nationalarchives.gov.uk/nelson/.

[10]Only 13.6% of our sailors are recorded in the muster roll as volunteers; an upper bound on the involuntary share is thus 86.4%. Seamen are 62.4% of all men in our sample, and only 17.8% of them are recorded as having volunteered, giving us our lower bound on impressment.

2.2 Machines

We derive measures of technology adoption from historical advertisements using 19th century local newspapers (British Library and Findmypast, 2022). When farms were sold, machines were typically sold with them. These would be listed in advertisements announcing the sale.[11] We identify seven labor-saving machines and three machines that did not save labor, using detailed descriptions of each machine's functionality in Fussell (1952) and based on whether the machines replaced work previously done manually (labor-saving) or not at all (non-labor saving). We complement these data with information from the *General Views of Agriculture*, government publications that detailed the agricultural conditions in each county of England around those years. In total, we have data on 4,875 machines – 3,878 labor-saving ones, and 997 non-labor saving ones (Figure 1-Panels C–D).

As Figure 1-Panels E–F show, machines can be found across the country. Thresher are the most common type (Panel C); the most common non-labor saving machines are turnip cutters and chaffing machines (Panel D). Figure 1-Panels E and F depict the geography of machine use. East Anglia and Cheshire saw massive adoption of both types of machinery. In the North, in Wales, and in Cornwall, non-labor saving machines made few inroads. London and its surroundings saw limited adoption, possibly because agriculture here catered to the city with garden crops.

2.3 Royal Agricultural Society Competitions

We gather data on the productivity of over 300 threshers from the records of the Royal Agricultural Society of England (RASE) competitions. Founded in 1840, the Society aimed to promote modern agricultural practices, organizing competitions to recognize the best designs of various agricultural machines (Brunt et al., 2012). We collect entries on the performance of 306 threshing machines presented at fifteen meetings between 1841 and 1872, deriving comparable measures of thresher productivity in sheaves/man/minute for threshed wheat. This novel database, along

[11] This dataset significantly expands Caprettini and Voth (2020), who tracked the adoption of threshers only, in 1800-30. We search British Library and Findmypast (2022) for nine more agricultural machines. We also examined more than 22,000 articles advertising the sale or the lease or a farm, and integrate the dataset with all machines found in these ads.

with earlier productivity data from the *General Views of Agriculture*, reveals a clear upward trend in average productivity despite substantial variation at any given moment (Figure 2).[12]

2.4 Other variables

We control for other local characteristics with data from several sources. Population, gender ratios and occupational shares come from the censuses of 1801 and 1811 (Southall et al., 2020).[13] We geolocate more than 19,000 farms whose sale or lease was advertised between 1800 and 1830 in one of the British newspapers (British Library and Findmypast, 2022). Distances are calculated from the centroid of every cell to the coast as well as to the closest point on the sea that is 15m deep, using the barymetric profile of the seabed in front of Great Britain (EMODnet Bathymetry Consortium, 2018). The list of commercial ports is from Alvarez-Palau et al. (2019) combined with a similar list of Royal Navy ports or anchorages from the Universal British Directory of 1791 (Barfoot and Wilkes) and *Three Decks*.[14] We integrate these sources with information from Lloyd's List for 1799-1800: it reported arrivals and departures of ocean-going ships weekly. This allows us to identify the major military and non military ports in terms of naval traffic. Data on 18th century English apprentices are from the Board of Stamp's Apprenticeship Books (see also Feldman and van der Beek, 2016). These volumes record duty payments for the employment of indentured apprentices. This helps us locate metal workers and watchmakers indentured between 1710 and 1791. We digitize the parish of origin of every inventor granted a British patent between 1700 and 1791 from Woodcroft (1854). Kanefsky and Robey (1980) compiled a comprehensive list of all the early steam engines in use in England since 1706 (mostly Newcomen engines): we geolocate the engines erected until 1791. Country banks are from Dawes and Ward-Perkins (2000): we control for the number of active banks in 1791. Wheat suitability is from FAO-GAEZ (Fischer et al., 2021), ruggedness from Nunn and Puga (2012)

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12 The final set of observations is for combined threshers, mapped on the right-hand $y-$axis.

13 We derive occupational shares from Question 3d of the 1801 census: "What Number of Persons, in your Parish, Township, or Place, are chiefly employed in Agriculture; how many in Trade, Manufactures, or Handicraft; and, how many are not comprized in any of the preceding Classes?".

14 See https://threedecks.org/. The site is maintained by scholars and naval enthusiasts.

and the bounty of the sea index is calculated with the method of Dalgaard et al. (2020) and data from Kaschner et al. (2013) and Food and Agriculture Organization (2016). We also use two more distances: to the closest town with a newspaper and to the nearest post office in 1791. Newspaper towns are derived from metadata of the corpus of historical journals (British Library and Findmypast, 2022). The list of post towns in 1791 is from Robertson (1961). Appendix A.2 provides details on variable construction.

3 Main Empirical Results

This section presents an overview of how military recruitment led to labor scarcity and its impact on technology adoption. Local recruitment caused gender imbalances. Labor scarcity strongly correlates with the adoption of labor-saving technologies, but not non-labor saving technology. Our IV strategy identifies the causal effect of labor shortages. Additionally, skill abundance reinforced labor scarcity in promoting technology adoption, which correlates with later productivity advances.

3.1 Preliminary Evidence

Did military recruitment lead to labor shortages? As a first step, we examine whether military recruitment was associated with greater gender imbalances. Figure A.2 shows the distributions of gender ratios in 1801 and 1811 as a function of military recruitment. More recruitment went hand in hand with a greater share of women: cells with above median recruitment rate have 2.6% and 3.6% more women per man in 1801 and 1811 respectively (peak recruitment is around 1811).

Wilitary recruitment is a strong and significant predictor of gender imbalances in both 1801 and 1811 (cols 1-3 and 4-6 of Table A.1). This is true unconditionally (cols 1 and 4), after controlling for the full set of controls (cols 2 and 5), and after adding region fixed effects (cols 3 and 6). Effects are large – col 3 (col 6) implies that doubling military recruitment increased gender imbalances in 1801 (1811) by 0.6 percentage points (1 percentage point).[15] Because gender ratios at birth are close to one, military recruitment created significant variation in labor shortages.

[15]This compares with an average of 4.9% and 5.9% more women per men in 1801 and 1811.

Internal migration did not equalize the distribution of missing men, as there were significant impediments to internal mobility (see Section 1.2).

In Figure A.3, we present a map of England showing the association between military recruitment and machine adoption. Blue locations indicate higher rates of labor-saving machine adoption; red, higher levels of Royal Navy recruitment. Where both coincide, the hexagon is darker overall. Light areas show either little recruitment or limited labor-saving machine adoption. While there are numerous blue and red observations, there are also many light, grey, and dark hexagons – areas where high recruitment coincided with high rates of labor-saving machine adoption, low recruitment with low adoption, or median recruitment and median adoption. Wales has mostly low levels of these two variables; East Anglia shows high levels of both in many cases. Areas with high/high and low/low values account for more than a third of all cells, 13% more than a random assignment would predict.

Figure 3 uses the method of Cattaneo et al. (2024) to show these patterns, for labor-saving and non-labor saving machines. For *labor-saving* machines in Panel A, there is a strong positive correlation with recruitment. The pattern is not evident for non-labor saving machines (Figure 3, Panel B).

3.2 OLS Results

To go beyond the graphical evidence, we estimate:

$$M_i = \alpha_r + \beta R_i + \boldsymbol{\gamma} X_i' + u_i$$

We are interested in β: the impact of military recruitment R in cell i on machine adoption M. X' is a vector of controls which includes other potentially important determinants of technology adoption. Demographic factors such as total population and the share employed in agriculture and trade in 1801 influenced the size of the agricultural sector and its demand for machines. Finance may affect farmers' ability to purchase new machines. We proxy for it with the presence of country banks in 1791. Local technological development may influence the introduction of new machines. We proxy for it using three indicators. The first identifies cells where between 1710 and 1791 at least one "mechanic" (e.g. wheelwrights, watchmakers and blacksmiths) received his apprenticeship. Second, we track the spread of steam engines in 1706-1791 (Kanefsky and Robey, 1980). Third, we analyze where local inventors filed a patent between 1700 and 1791 (Woodcroft, 1854).

We control for geographic factors, such as area, wheat suitability (Fischer et al., 2021), ruggedness (Nunn and Puga, 2012), access to fisheries (Dalgaard et al., 2020), and distance to the nearest post office town in 1791, which may influence machine profitability. Additionally, towns publishing newspapers likely serve as centers for diffusing new ideas, facilitating adoption in nearby areas. To address potential over-sampling of areas covered by local papers (Beach and Hanlon, 2022), we control for the total number of farm ads, which are more numerous than machine ads (19,280 vs 4,875), and the distance to the nearest town with a newspaper. In the most conservative specification, we include five region fixed effects α_r to account for potentially varying labor market conditions across England (Caird, 1852).[16]

Table 1 explores the basic patterns, conditional on an expanding set of control variables. We use 2,600 equally-sized cells covering England and Wales as units of observation. Panel A reports estimates for labor-saving machines. We find a large and highly significant effect of recruitment on labor-saving technology adoption across all specifications. This is true for the basic OLS specification (col 1), as well as across the increasing set of controls (cols 2-4). In the last two columns, we estimate separately the impact of navy (col 5) and army recruitment (col 6); both promoted technology adoption, though the army had a somewhat larger impact.

The effects are large. Our baseline result suggests that a one standard deviation (s.d.) increase in recruitment per capita raised labor-saving machine adoption by 0.2 of a s.d. Once we control for other variables, the size of the coefficient declines, but remains large and significant even in the most demanding specifications. Controlling for other farm ads reduces the coefficient the most (col 2): this is to be expected as machine ads are a subset of total farm ads. Additional controls only lead to minor changes in coefficient size, alleviating concerns over omitted variables.

[16] We include log-transformed recruitment, population, and farm ads due to their skewed distributions, assigning -2 to the log of 0 to ensure observations with 0 receive the lowest value (Chen and Roth, 2023). As a dependent variable, the extensive margin is valued at 200 log points. We also demonstrate that our conclusions are robust to alternative assumptions.

Recruitment is a weaker predictor of the adoption of non-labor saving machines. For these technologies, unconditional OLS estimates also suggest a significant effect, but of a smaller magnitude of 0.1 standard deviations (Panel B, col 1). However, once we control for other variables, the coefficient becomes statistically insignificant and is close to zero (cols 2-4). When we investigate the impact of recruitment across different branches of the military, we find no effect for the Royal Navy (col 5). In contrast, recruitment of soldiers by the British Army had a positive and significant impact on the adoption of non-labor saving machines. However, the point estimate of army recruits is one-third of the coefficient for labor-saving technology in Panel A. In a test of equality of the effect between the coefficients of labor saving and non-labor saving machines, we reject the null of identical coefficients in all specifications ($p = 0.02$ or lower, reported in the second last row of the table). Thus, it is clear that military recruitment does not always correlate with technology adoption: war-induced labor shortages mostly led to the diffusion of machines biased to save labor.

3.3 IV results

The OLS results could be biased for several reasons. We observe only a fraction of total recruitment; large measurement error may introduce downward bias. Moreover, unobservable characteristics correlated with both recruitment and adoption may add further bias. For example, if recruitment efforts were less intense in rural areas and if they targeted non-agricultural workers, our estimates would be downward biased. This bias would be particularly severe in the case of naval recruitment, which was concentrated in trading ports and sought men with seafaring experience (not rural workers). In order to establish a causal link we need additional evidence. Here we present an IV strategy that exploits plausibly exogenous variation in recruitment.

We focus on navy recruitment and construct an instrument as the shortest distance to deep, navigable sea. To avoid confounding the effect of distance to the deep sea with proximity to the coast, we condition on the distance to the coast and restrict the IV sample to coastal areas. The resulting IV strategy is depicted in Figure 4. We first discuss the logic of the instrument and then present several exercises supporting the validity of the strategy.

Intuition. Our IV strategy is based on the decentralized nature of Royal Navy recruitment, where captains were responsible for manning their own ships using incentives and force. Impressment, accounting for at least half of all sailors (Rodger, 2006), involved Royal Navy ships stopping merchant vessels or sending press gangs to raid local pubs and gathering places. To press men, navy vessels would anchor out at sea and send smaller boats to reach the nearest beach.

Our instrument is the ease with which these boats could reach any coastal location. Rowing or sailing small boats over the open sea was only feasible for limited distances. Because most naval recruitment was carried out by ships much larger than civilian ships, we can separate military labor demand from that of the merchant marine, avoiding the concern that focusing on maritime districts may simply reflect trade effects. Our instrument is based on the technical characteristics of military ships in the Age of Sail. Ships of the line had a draft of around 10m and typically anchored at a minimum depth following the FUD rule (Figure A.4), translating to 14-16m for first-rate to third-rate ships.

To avoid confounding our effect with proximity to the sea, we restrict our sample to coastal cells within 15km from the coast and control for the distance to the coast. We then use distance to the deep sea, defined as the shortest path from the cell centroid to the closest point of the seabed 15m below the waterline (Figure 5-Panel A). In this coastal sample, the farther the 15m line is from the coast, the lower the probability of an area being home to a Royal Navy port (Panel B). The exclusion restriction requires that, within our sample of coastal cells and conditional on the distance to the coast, the distance to the closest point at which the seabed drops to 15m affects adoption of agricultural machines only

To build intuition, consider two ancient hundreds – Clackclose and Smithdon in Norfolk (in blue and red in Figure 5–Panel C). Both lie on the mouth of the Great Ouse within 32 km from each other, on fertile coastal land (wheat potential yield is 4.1 kg/ha), and in 1801-11 were home to around 1,000 people. Most of those employed worked in agriculture: 41 percent in Clackclose and 42 percent in Smithdon; the share of people in trade was 4-5 percent. Both cells scarcely had access to finance or advanced technology: until 1791 we find no country bank, no mechanic apprentice, no British inventor, and not a single Newcomen steam engine. However, Smithdon faces the deep sea of East Anglia while Clackclose lies on shallow waters of the Great Ouse estuary, 16 times as far from the deep sea (2.4 vs 39 km). The Royal Navy recruited in Smithdon but not in Clockclose, resulting in greater gender imbalances (1.05 vs 1 women per men) and faster technology adoption: we find twice as many labor saving machines in Smithdon (14 vs 7). Our IV strategy extends this comparison to the full sample of coastal cells.

Validation. Our IV-strategy is plausible for four reasons. First, Table A.2, col 1 shows a strong, significant effect of distance to the deep sea on the probability of a navy port, with every doubling of distance reducing it by 10.5%. The same is not true of commercial ports (col 2). To identify the busiest ports, we digitize two years of Lloyd's list, tracking every ocean-going vessel sailing to or from British ports. The top 15 ports account for 95% of the country's traffic. Moreover, for six of these ports military ships account for more than a quarter of all ships movements:[17] distance to these ports is significantly correlated with distance to the deep sea (col. 3 Table A.2). In contrast, distance to deep sea does not correlate with distance to the other nine commercial ports.

Second, we predict the presence of navy ports with distances to alternative sea depths, from 5m to 25m. Figure 5–Panel D plots the coefficients and confidence intervals from a regression that includes all of these distances: only the 15m deep contour line predicts navy presence, and the coefficient is significantly different from all other depths ($p \leq 0.037$). This is consistent with the technical requirements of large Royal Navy vessels, for which only the 15m depth mattered.

Third, we investigate the impact of the distance to the deep sea on coastal recruitment across the two military branches. Cols 1–2 of Table 2-Panel A suggest a strong correlation between Royal Navy recruitment and deep sea: the closer an area to deep, navigable sea, the higher the navy recruitment rate. In contrast, the Army was not constrained by coastal depth and cols 3–4 of the same table confirm that distance to deep sea and army recruitment are unrelated (these coefficients are

[17]These are: Deal, Portsmouth, Plymouth, Falmouth, Yarmouth and Torbay: all except Plymouth and Torbay have more than 55% of military traffic.

significantly different from each other: $p \leq 0.006$).

We also partition naval recruitment based on the depth of ships' hold and ask whether distance to the deep sea mattered more for ships with deeper draught. Appendix Figure A.6–Panel A provides suggestive evidence that this is the case: distance to the deep sea is a stronger predictor of those recruited into larger ships.[18] Appendix Table A.3 shows regressions with controls (cols 1–2) and with controls and region fixed effects (cols 3–4). For large ships, the coefficient of deep sea is between two and three times as big as that for shallow ships, and the difference is significant in the first two columns ($p = 0.02$) though not in the last two ($p = 0.24$). In combination, these results provide clear support for our identification assumptions.

Appendix Figure A.6–Panel B analyzes the balance of our instrument. We report β-coefficients from separate regressions where we correlate demographic, economic and geographic characteristics with the distance to the deep sea. In each regression we include only coastal cells and control for the distance to the coast, asking whether distance to the deep sea has additional predictive power. Two results stand out. First, larger and more populated cells are farther from the deep sea. This result is likely a product of the way we construct our grid: cells partially covered by sea have smaller land area and are home to fewer people. They are also closer to the deep sea.[19] A better indicator is the fact that density (log people per square meter of land) is not correlated with the instrument, which suggests that the significant correlation with population and area may be mechanical. Second, areas farther from the deep sea are more suitable to wheat farming. We control for wheat suitability in all our specifications and note that, if anything, this correlation works against our mechanism – wheat suitability is important for thresher adoption (Caprettini and Voth, 2020). Therefore, areas less exposed to naval recruitment have higher incentives to adopt cereal-processing machinery (e.g. threshers). The other observ-

[18] We consider ships with a deep draught those with a depth of the hold of 5m or more: they are overwhelming ships of the line (90 out of 92). Sloops, frigates, cutters, gun-brig and schooners are all ships with a shallow draught. For this exercise we also consider only recruits with fewer than three years of sea experience (landsmen and ordinary seamen). This excludes officers (who joined voluntarily) and experienced sailors who are likely to have rotated in from a different ship and for whom the current vessel would not be informative of the ship which they initially joined.

[19] Indeed, because cells are equally sized, they vary in area only because some are partially covering the sea.

ables shown in Figure A.6–Panel B are remarkably balanced with the instrument. Together with the absence of a correlation with commercial ports and army recruitment, these results strongly suggest that our IV strategy is plausible.

IV estimates. Table 2 reports IV results. Panel A, cols 1–2 show the first stage: distance to the deep sea strongly predicts naval recruitment: A one s.d. increase in distance to the deep sea reduced naval recruitment by 0.14 to 0.18 s.d. The first-stage is strong, with an F-stat of 16-30, well above the customary cut-off of 10. As discussed above, distance to deep sea has no effect on army recruitment (cols 3–4). Panel B presents the reduced form. Areas farther from the deep sea adopted fewer labor-saving machines (cols 1–2). The same is not true for non-labor saving machines (cols 3–4). Finally, Panel C reports two-stage least squares estimates: We find a large and significant impact of recruitment on labor-saving machine adoption (cols 1–2). The Anderson-Rubin statistics has $p \leq 0.001$, and 5 and 10% confidence intervals calculated with tF method of Lee et al. (2022) do not include zero, demonstrating the strength of our instrument (Panel D). The coefficients indicate that increasing naval recruitment by 1 s.d. led to a 0.57-0.92 s.d. increase in the number of labor-saving-machines – a substantial effect. The same effect is not visible for non-labor saving technology (cols 3–4): we cannot reject the null of no effect, and the coefficients are significantly different from the ones in cols 1–2 ($p \leq 0.003$).

Never takers. One simple way to further validate our IV-exercise is to look at never-takers, in the spirit of D'Haultfœuille et al. (2021). If the exclusion restriction holds, then areas of Britain without naval recruitment should *not* show any effect of distance to the deep sea on adoption: where there are no "compliers", our instrument should have no predictive power for the adoption of labor-saving machines. Table A.4 col 2 confirms that never-taker areas – areas without naval recruitment – show no effect of deep sea distance on the adoption of labor-saving machines.

Size of IV vs OLS. Compared with OLS, our IV-coefficients increase markedly in size: Downward bias in the OLS is likely to explain this difference.[20] There are two

[20]We find limited evidence of significant differences in compliers: Appendix Table A.5 uses the method of Marbach and Hangartner (2020) to show that compliers are similar to the rest of the sample. This suggests that the LATE uncovered by IV should not differ too much from ATE effects estimated by OLS.

likely sources of bias. First, severe measurement error stems from sampling – we only have muster rolls for about 1/3 of ships, and of the individual sailor entries, only 30% contain precise information on geographical origin. Additionally, records are derived from hand-written documents kept by clerks with few incentives to give uniformly detailed, accurate information on the geographical origin of sailors. This noise alone may explain a large share of the OLS-IV difference: Figure A.7 plots error-in-variables OLS estimates against different levels of reliability in recruitment. Reliability lower than 30% (not implausible given the nature of the data) would explain the entire OLS-IV difference. Second, omitted variables are likely to introduce further downward bias. To see this, recall that the navy preferred to recruit sailors in trading centers: areas with a larger population, pubs, a relatively small agricultural sector, and little need for threshers and similar machines. Our IV sidesteps this issue because it identifies the effect of recruitment in areas where the navy recruited for exogenous reasons (deep sea). In sum, noise in our explanatory variable and unobservable confounders can rationalize significant downward bias in the OLS and help to explain the substantial difference between OLS and IV.

3.4 Synergies with other drivers of growth

Labor scarcity is not the only explanation of the British Industrial Revolution: in this section we explore synergies between labor shortages and other important factors contributing to Britain's takeoff.

In addition to Allen's hypothesis, the most prominent theory of the Industrial Revolution emphasizes the role of human capital (Mokyr, 2009). Mechanics were particularly important for developing new machines and for maintaining them. From apprenticeship records, we collect data on the geography of mechanical skills before the outbreak of the Napoleonic Wars. These additional data allow us to identify a clear synergy – areas of Britain home to craftsmen with mechanical training show faster adoption of labor-saving machines when labor is scarce.

Figure 6 presents the basic patterns. Panel A shows that the probability of adopting a labor-saving machine is higher in places with mechanical (wheelwright or watchmaking) apprentices than in areas without them; and where there is more than one such apprentice, the rate of adoption is almost three times as high as in areas without any skilled trainee. Because the sample only includes rural cells, the difference is not driven by ease of adoption in urban centers. Panel B shows the interaction with recruitment. While recruitment correlates positively with adoption across the sample, in areas with at least two skilled apprentices the relationship is markedly steeper. The availability of local mechanics facilitated technology adoption in response to military recruitment, causing more labor-saving machine adoption where numerous mechanics were available.

In Table 3, we show that the synergy between metal-working apprentices and labor shortages leading to labor-saving machine adoption is statistically significant – recruitment correlates with adoption significantly more when there were at least two skilled mechanics with full controls (col 3) and with controls and region fixed effects (col 4). There is no such pattern for non-labor saving machines (cols 7-8), whose adoption was less influenced by labor scarcity. These results suggest that both factor scarcity and human capital availability were important factors for technology adoption both individually and in combination. In other words, it does not appear that the two main theories of the Industrial Revolution are mutually exclusive (Allen, 2009; Mokyr, 2009): they may in fact have reinforced each other.

Additional factors such as coal, finance and slave wealth also contributed to British growth during the 19th century. We investigate synergies in Appendix Table A.6. The first two columns look at coal, using the presence of carboniferous deposits as in Fernihough and O'Rourke (2021). The next two columns explore the role of country banks (Heblich and Trew, 2019), and the last two that of slave wealth, proxied by proximity to one of the major slave ports (Heblich et al., 2022). Coal presence correlates negatively with machine adoption (col 1) and dampens the impact of labor scarcity on adoption (col 2). In 1830 steam engines were almost non-existent in agriculture[21] and it is likely that coal mines reduced the importance of the agricultural sector. In contrast, we find a strong positive interaction between country banks and labor shortages (col 4): when finance was easily available, farmers were quick to respond to labor scarcity by adopting labor saving machines. Finally,

[21]For example, none of the machines in our database was steam-powered.

cols 5 and 6 show no synergy with proximity to slave ports, possibly because slave wealth was concentrated in the hands of relatively few individuals, while adoption was much more widespread.

Two results stand out. First, labor scarcity is an important driver of adoption even after accounting for other key factors behind Britain's growth. Second, labor scarcity shows important synergies with finance and human capital. Farmers experiencing labor shortages turned to labor saving machines much more when they could easily access finance and when they lived in communities where mechanical skills were abundant.

3.5 Technological improvements

Did induced adoption in areas with labor shortages matter for the pace of subsequent technological improvements? We focus here on threshing machines because of the unique data provided by the RASE competitions on the process of invention. Table 5 shows adoption and recruitment predict productivity of entrants' designs. We find that more machines in a county lead to more productive average machines in RASE competitions, suggestive of learning-by-doing effects. This pattern holds for both OLS and IV, with larger effects from the IV estimation. We find large effects for overall and for navy recruitment (cols 3–4). When we instrument for navy recruitment (col 5), we also see a large effect, and distance to the deep sea directly predicts markedly lower productivity of machines entered in RASE competitions (col 6). These results suggest that where more threshing machines were adopted, tinkering was more common – and more inventors competed at RASE meetings. This helped to refine the technology, increasing productivity over time.

4 Alternative Explanations and Robustness

We examine alternative explanations as well as the robustness of our results.

4.1 The role of commercial ports and the land market

There are two potential confounders of our results: commercial shipping and the land market.[22] First, one alternative interpretation of our results is that military recruitment had no major, differential impact on labor shortages as such. Instead, all ports in England boomed during a period of maritime warfare, siphoning off labor. To account for this, we digitize data on shipping traffic from Lloyd's List, a periodic publication tracking the arrival of large ships, both military and non-military, in British harbors (and select foreign locations). We collect data on the frequency of use of each port by navy and civilian ships throughout the years 1799–1800, at the height of the Napoleonic Wars. Ports with more than 25% of all traffic by Royal Navy ships we catagorize as "naval."[23]

First, we evaluate the extent to which the Royal Navy and the merchant navy used the same ports. The top six naval ports account for 94% of all 1799-1800 Royal Navy vessels. Those ports were also visited by 5,370 commercial ships, equivalent to only 29% of all commercial traffic. In contrast, the busiest non-military ports handled 66% of all commercial shipping, and received less than 4% of all Navy vessels. Second, the biggest commercial ships were considerably smaller than the first-rate ships-of-the-line of the Navy: for instance, when the Royal Navy purchased the largest East Indiaman, it converted them to a fourth-rate ship. The difference in size between military and commercial ships explains why the location of commercial ports was not influenced by the distance to the 15m bathymetric line: As cols. 3 and 4, Table A.2 show, distance to the deep sea correlates strongly with distance to military ports, but not with distance to commercial ports. In sum, navy and commercial ships had different sizes and used distinct ports: these differences why depth requirements differed.

Finally, we re-estimate adoption regressions, controlling for distances to major commercial ports (Table A.7). Reduced form results are not affected; IV results are strengthened if we control for distances to major commercial ports.

[22] We thank our NBER discussant, Gordon Hanson, for highlighting the potential importance of these points.

[23] These data complement information on ports used in Section 3.3 because it records information on actual naval traffic and allows us to zoom in on the most important ports.

Reverse causality is also a theoretical possibility: Naval recruitment may have created labor shortages, driving up the cost of labor and in turn, making farm sales (where machinery would then be listed), more likely. To address this potential concern, we geolocate more than 19,000 advertisements publicizing the sale or lease of a farm between 1800 and 1830.[24] This also covers farms that had no machines on their premises. We add the total number of farm ads to our specifications, thus controlling for state of the land market at the beginning of the 19$^{\text{th}}$ century – without any effect. Additionally, in Appendix Table A.8 we estimate reduced form and IV with log total farm ads or a dummy for at least one farm ads as dependent variables. Results differ starkly from machine adoption: reduced form and IV estimates have the wrong sign, are close to zero and not significant. These results suggest that the impact of recruitment on the land market is unlikely to confound our results.

4.2 Robustness Checks

In Appendix B we demonstrate that our results are robust to several checks. Section B.1 discusses results when we predict the extensive margin of technology adoption or when we estimate discrete choice models. Section B.2 presents results from matching exercises and Section B.3 explores the robustness of inference to spatial autocorrelation. Section B.4 shows the robustness of IV results to violations of the exclusion restriction using the method of Conley et al. (2012) and Section B.5 re-estimates the models with alternative samples and definition of our main variables. Our conclusions survive all of these robustness checks.

5 Conclusion

Britain was the first country to break free from Malthusian constraints, shifting most of its workforce from agriculture to industry. This shift occurred while Britain had unusually high wages and against a background of frequent wars – between 1700 and 1815, at the start of the Industrial Revolution, Britain fought on average in one year out of three (Brewer, 1988). Britain was also home to a large number of scientists

[24] We search British Library and Findmypast (2022) for the exact words "farm auction," "farm sale," "farm for sale," "farm to be let," "farm to be sold," and "farm to sell."

and "tinkerers" – men from all walks of life whose public standing depended on their ability to improve technology (Mokyr, 2009).

In this paper, we argue that these three important features are closely connected, and facilitated the transformation of the British economy: Wartime labor shortages boosted technology adoption in industrializing Britain. Greater use of technology, in turn, induced improvements in machinery, possibly through "learning by doing." We isolate this mechanism using detailed data from the Napoleonic and Revolutionary Wars, the most protracted and costly war Britain fought before 1914. Over a quarter of a century, Britain maintained the largest navy of all European powers and a sizeable army. Sailors and soldiers were not available to work in the fields and factories. In places with heavy recruitment, the adoption of a critical labor-saving technology – threshing – and other labor-saving machines took off. The same is not true of non-labor saving machines.

After the end of the wars, when men returned from war, the new machinery remained in place. Efficiency (and reliability) improvements were one reason. Data from agricultural competitions show that in places where machines had been used more due to naval recruitment 1793-1815, the scale of 'tinkering' and the pace of progress was faster. As Allen (2009) argued, adopting new technologies responded to factor scarcity. However, the artisans and experimenters highlighted by Kelly et al. (2022) also contributed to faster technological progress. Much recent work on industrialization has pitted the 'factor scarcity' view against the 'culture and skill-base for invention' interpretation. Our results suggest a unified interpretation, documenting an important synergy between exogenously-induced labor scarcity and mechanical skills; where a confluence of both occurred, technology advanced faster.

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Tables

Table 1: OLS evidence: Labor-saving and non-labor saving machine adoption

Panel A: Labor saving machines and recruits

	Labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
log total recruits p.c.	0.375***	0.122***	0.121***	0.106***		
	[0.045]	[0.039]	[0.038]	[0.038]		
log Royal Navy recruits p.c.					0.084**	
					[0.041]	
log British Army recruits p.c.						0.154***
						[0.046]
R^2	0.039	0.260	0.267	0.287	0.286	0.290
Mean. dep. var.	1.490	1.490	1.490	1.490	1.490	1.490
Demography, area, soil and farm ads	No	Yes	Yes	Yes	Yes	Yes
Technology, skills, finance and geography	No	No	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	Yes	Yes	Yes
Observations	2603	2603	2603	2603	2603	2603

Panel B: Non labor saving machines and recruits

	Non labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
log total recruits p.c.	0.088***	0.015	0.014	0.012		
	[0.017]	[0.016]	[0.015]	[0.015]		
log Royal Navy recruits p.c.					-0.004	
					[0.017]	
log British Army recruits p.c.						0.045**
						[0.018]
R^2	0.015	0.124	0.132	0.134	0.133	0.136
Mean. dep. var.	0.383	0.383	0.383	0.383	0.383	0.383
Demography, area, soil and farm ads	No	Yes	Yes	Yes	Yes	Yes
Technology, skills, finance and geography	No	No	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	Yes	Yes	Yes
p-value lab sav = non lab sav	0.000	0.002	0.002	0.006	0.019	0.007
Observations	2603	2603	2603	2603	2603	2603

Notes: OLS estimates of Equation (1). Panel A: dependent variable is labor saving machines in 1790-1830. Panel B: dependent variable is non-labor saving machines in 1790-1830. Units of observation are 2603 equally sized hexagonal cells. The p-value at the bottom of the table tests the null that the coefficients in Panels A and B are the same. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table 2: First stage, reduced form, and two-stage least squares (coastal sample)

Panel A: First stage

	log recruits p.c.			
	(1) Royal Navy	(2) Royal Navy	(3) British Army	(4) British Army
Distance to deep sea	-1.128***	-0.881***	0.236	-0.038
	[0.205]	[0.222]	[0.199]	[0.210]
R^2	0.261	0.293	0.124	0.134
Mean. dep. var.	-0.277	-0.277	-0.943	-0.943
F-stat of excluded instrument	30.3	15.8		

Panel B: Reduced form

	Machines			
	(1) Lab sav	(2) Lab sav	(3) Non lab sav	(4) Non lab sav
Distance to deep sea	-1.102***	-1.397***	0.052	-0.156
	[0.309]	[0.347]	[0.119]	[0.143]
R^2	0.284	0.300	0.119	0.133

Panel C: Two-stage least squares

	Machines			
	(1) Lab sav	(2) Lab sav	(3) Non lab sav	(4) Non lab sav
log Royal Navy recruits p.c.	0.977***	1.585***	-0.046	0.177
	[0.323]	[0.535]	[0.104]	[0.167]
Mean. dep. var.	1.442	1.442	0.342	0.342
Distance to coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes
Anderson-Rubin test (p-value)	0.000	0.000		
Observations	886	886	886	886

Panel D: tF Inference

Machines (column):	tF Inference	
	5%-level	10%-level
Labor saving (1)	[0.223, 1.730]	[0.439, 1.514]
Labor saving (2)	[0.096, 3.073]	[0.578, 2.591]
Non labor saving (3)	[-0.289, 0.196]	[-0.220, 0.127]
Non labor saving (4)	[-0.289, 0.642]	[-0.138, 0.491]

Notes: Sample consists of 886 cells within 15 km from the coast. Dep. var.: Panel A: Navy recruits p.c. (i.h.s., cols 1–2) and Army recruits p.c. (i.h.s., cols 3–4). Panels B and C: labor-saving machines (cols 1–2) and non-labor saving machines (cols 3–4). Panel D: 5% and 10% confidence intervals for IV estimates in Panel C calculated with Lee et al. (2022) method. Panel A–C: robust s.e. in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Adoption: Synergies between mechanics and labor scarcity

	Labor saving machines				Non labor saving machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log total recruits p.c.	0.115***	0.102***	0.048	0.030	0.013	0.011	-0.002	-0.005
	[0.037]	[0.038]	[0.035]	[0.034]	[0.015]	[0.015]	[0.014]	[0.014]
Tot recruits pc × one mechanic			0.021	0.001			0.012	0.011
			[0.074]	[0.072]			[0.037]	[0.037]
Tot recruits pc × > 1 mechanics			0.330**	0.367**			0.069	0.072
			[0.145]	[0.144]			[0.056]	[0.056]
One mechanic	0.002	-0.126	0.034	-0.092	-0.022	-0.023	-0.017	-0.018
	[0.110]	[0.113]	[0.108]	[0.110]	[0.052]	[0.054]	[0.050]	[0.053]
> 1 mechanics	0.744***	0.498***	0.580***	0.302*	0.117*	0.109	0.084	0.072
	[0.161]	[0.167]	[0.163]	[0.165]	[0.065]	[0.069]	[0.066]	[0.070]
R^2	0.274	0.292	0.278	0.297	0.133	0.135	0.134	0.136
Mean. dep. var.	1.490	1.490	1.490	1.490	0.383	0.383	0.383	0.383
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2603	2603	2603	2603	2603	2603	2603	2603

Notes: Heterogeneity in the effect of labor scarcity on machine adoption by metal apprentice presence. OLS estimates of Equation (1) with interaction between military recruits and mechanic apprentices. Dep. var.: labor-saving machines (cols 1–4) and non-labor saving machines (cols 5–8). Units of observation are 2603 equally-sized cells. All regressions include the full set of controls. In cols 3-4 and 7-8 we add five region fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Technological progress. RASE competitors, adoption and skill abundance

	RASE entries, 1841-72			
	(1)	(2)	(3)	(4)
	Number	Number	Dummy	Dummy
log threshers within 8Km	0.045**	-0.009	0.002	-0.003
	[0.019]	[0.019]	[0.002]	[0.002]
log threshers within 8Km × one mechanic		0.025		0.004
		[0.029]		[0.005]
log threshers within 8Km × >1 mechanic		0.167**		0.015**
		[0.081]		[0.006]
One mechanic	-0.055	-0.063*	-0.004	-0.005
	[0.041]	[0.036]	[0.005]	[0.006]
> 1 mechanics	0.174*	0.020	0.021***	0.007
	[0.089]	[0.086]	[0.007]	[0.008]
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
R^2	0.033	0.037	0.063	0.067
Mean dep var	0.110	0.110	0.015	0.015
Observations	2775	2775	2775	2775

Notes: Early adoption, skill abundance and participants to RASE competitions. OLS estimates. Dep. var.: number of RASE participants (cols 1–2) and at least one participant dummy (cols 3–4). Sample consists of 2,775 equally sized hexagonal cells and includes urban cells. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

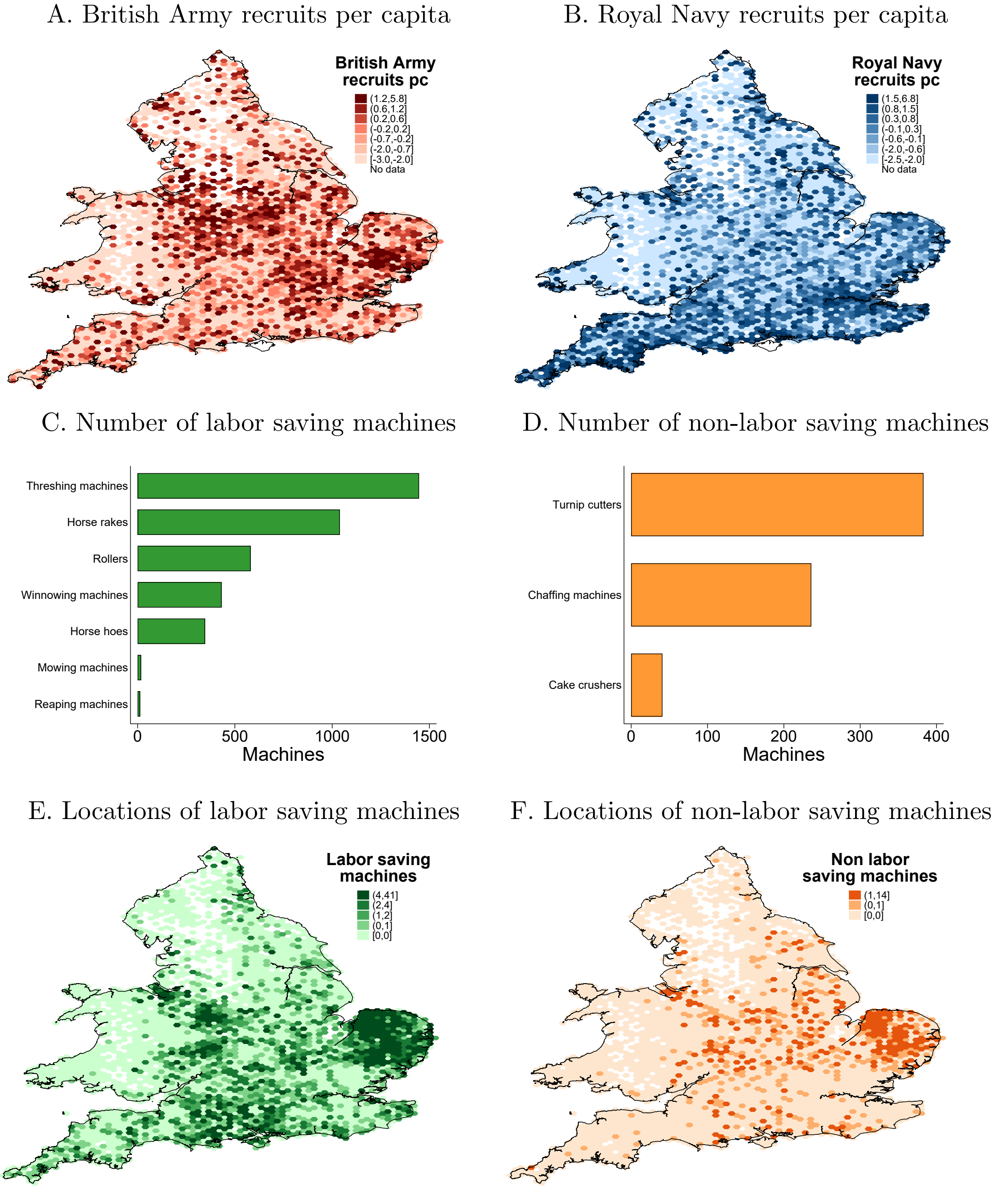
Table 5: Productivity of Thresher Designs and Its Determinants

	Productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	OLS	IV	RF
Threshers within 50 km	0.006***	0.008***				
	[0.002]	[0.002]				
log total recruits p.c.			0.735**			
			[0.277]			
log Royal Navy recruits p.c.				0.440**	1.101***	
				[0.184]	[0.366]	
Distance to deep sea						-1.922***
						[0.588]
R^2	0.520	0.009	0.518	0.516	0.004	0.521
Mean dep var	2.658	2.658	2.658	2.658	2.658	2.658
Distance to coast	No	Yes	No	No	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306	306	306	306	306	306

Notes: Early adoption and productivity of threshers. OLS estimates. Dep. var.: productivity of steam-powered threshers (sheaves per worker per hour). Sample consists of 306 steam-powered threshers in RASE competitions. Robust s.e. in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

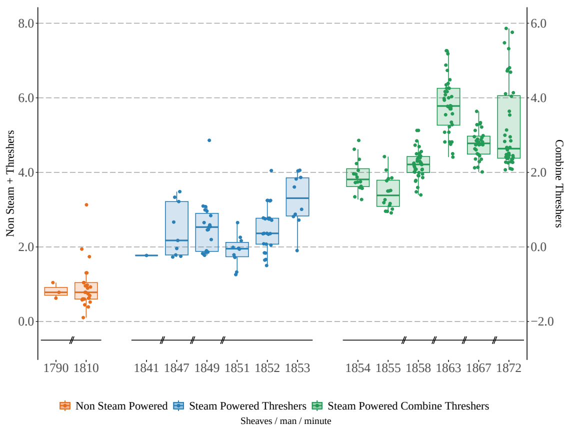
Figures

Figure 1: Military recruitment and machine adoption during the Wars against France



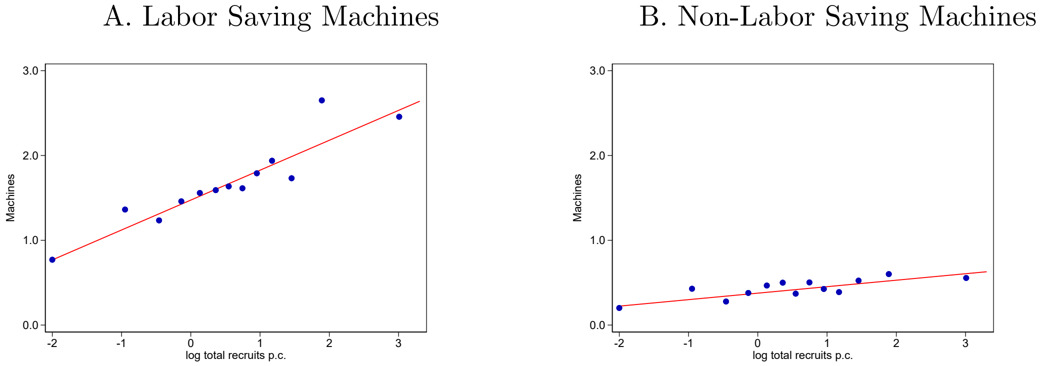
Notes: Panel A: log British Army recruits in 1790s-1810s per 1801 population. Panel B: log Royal Navy recruits in 1792-1815 per 1801 population. For both measures, we follow Chen and Roth (2023) and assign -2 to places with no recruits. Panels C–F: frequency and location of agricultural machines. Sources: Army: Floud et al. (1990); Navy: Trafalgar project, Dancy (2018) and Muster rolls; Machine adoption: British Library and Findmypast (2022) and *General Views of Agriculture*.

Figure 2: Productivity of threshing machines: 1790-1872



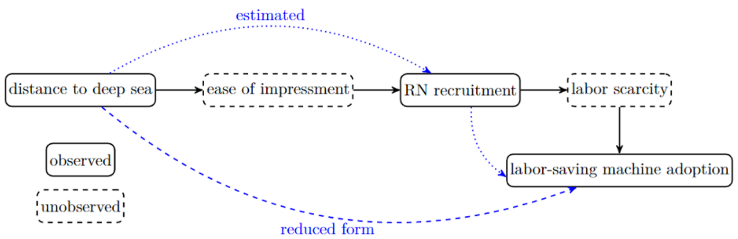
Notes: Productivity of threshing machines in sheaves of wheat threshed by worker man in one hour. One sheaf of wheat weighs roughly 1.5kg. *Sources*: 1790s and 1810s: *General Views of Agriculture*; 1841-1872: Royal Agricultural Society of England competitions.

Figure 3: Military recruitment and machine adoption



Notes: Military recruitment and machine adoption. Unconditional binscatters with average number of agricultural machines (y-axis) against bins of log total recruitment (x-axes). We use Cattaneo et al. (2024) Stata package `binsreg` to draw binscatter. Panel A: labor-saving agricultural machines. Panel B: non-labor saving agricultural machines.

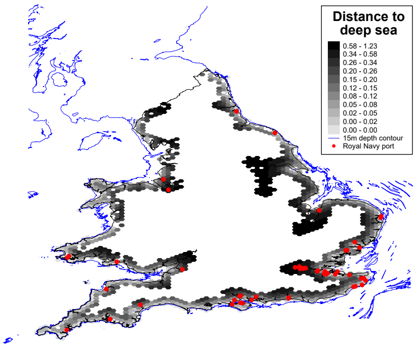
Figure 4: IV Strategy



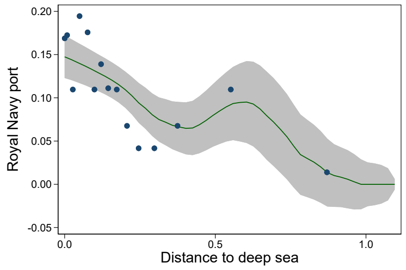
Notes: The figure summarizes the IV-strategy. Solid black arrows indicate hypothesized causal links. Dashed blue lines indicate reduced form relationships; dotted blue lines, estimated ones.

Figure 5: IV strategy

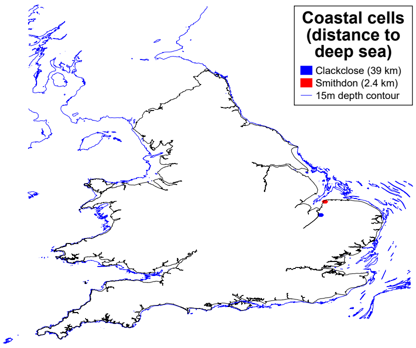
A. Deep sea and port location



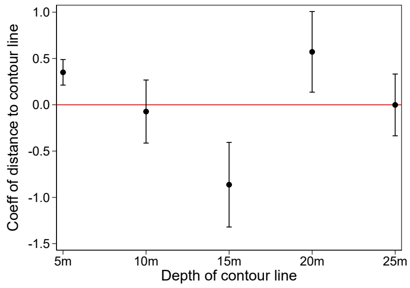
B. Navy presence and distance to deep sea



C. Example: cells with different IV exposure



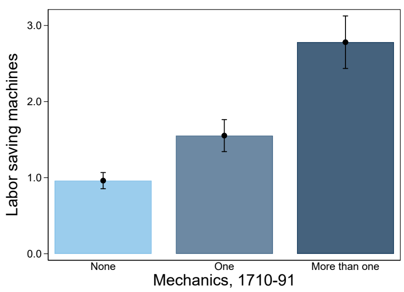
D. Distance to deep sea and Navy presence



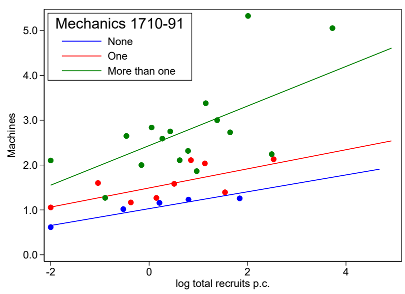
Notes: Panel A: distance to the closest sea point 15m deep; in red Royal Navy ports. Panel B: unconditional relationship between distance to the deep sea (x-axis) and Royal Navy port presence (y-axis). Kernel-weighted local polynomial smoothing lines and 95% CI. Panel C: location of two cells used for illustration in the text. Panel D: coefficients of distances to closest sea points of depths ranging from 5m to 25m. Dependent variable is Royal Navy port; we control for distance to coast, the full set of controls and region fixed effects. We use robust standard errors to draw 95% CI. The sample for Panels A, B and D consists 886 cells within 15 km from the coast.

Figure 6: Technology adoption and mechanics

A. Machine adoption and mechanics



B. Adoption, labor scarcity and mechanics



Notes: Panel A: labor-saving machines by presence of mechanics: mean and 95% CI. Panel B: labor scarcity and machine adoption by presence of mechanics. Unconditional binscatters of log total recruits (x-axis) on labor saving machine adoption (y-axis) in three samples defined by the number of mechanics. We use Cattaneo et al. (2024) Stata package `binsreg` to draw binscatter.

Appendix for Online Publication

A Data Appendix

We work with two main databases: one of hexagonal cells covering England and Wales, and one of British thresher producers who took part in the Royal Agricultural Society competitions between 1841 and 1872. In this appendix we first describe the construction of these two databases and then provide details on each variable used.

A.1 Unit of analysis

Hexagonal cells. We start from a georeferenced map of England and cover it with a grid of identical hexagonal cells of 120 square km each (function "fishnet" on ArcGIS). The cells are our main unit of observation, and we define all variables on them. We have two types of variables: geographical and demographic/economic. Geographical variables include distances (e.g. to the coast, to towns publishing newspapers, ...) and land characteristics (area, wheat suitability). We calculate geographical variables using the coordinates of the centroid and borders of each hexagon. For instance: distances are calculated from the centroid of the hexagons, and we compute wheat suitability inside each cell's area. The demographic/economic variables are sourced from various historical documents listed below, originally recorded at the level of the ancient parishes. There are around 10,000 such parishes, and we assign them to hexagons based on where the parish centroid falls.

There are 3,149 hexagonal cells in English and Wales. From these, we exclude cells with zero 1801 population (71) and no information on sectoral employment shares (2). We also drop urban areas: cells with log density greater than -9 (177). Finally, we deal with issues arising from newspaper-based variables (Beach and Hanlon, 2022) by restricting the sample to only cells within 50 km from an historical newspaper. We augment this condition by requiring that cells contain parishes that are mentioned in English newspapers at least once between 1790 and 1830. The 50 km condition drops 279 (mostly Welsh) cells and the mention condition drops an additional 17. This leaves us with 2,603 cells: our baseline sample. The IV analysis further restricts the sample to coastal areas: 886 cells satisfy all previous conditions and lie within 15 km from the British coasts.

Producers. In 1841 the Royal Agricultural Society of England started awarding prizes for the best steam-powered threshing machine presented during one of its meetings. Between 1841 and 1872, 309 threshers and 67 producers took part in fifteen separate competitions. During these competitions, the producers of these threshers processed a fixed amount of wheat, while inspectors recorded the performance of each machine. The best machine received a prize which could reach £60 but was usually around £20-25. We find the complete results of these competitions and collect measures of machines' productivity. We allocate these machines to the parish where the firm that produced them operated: a piece of information which we find either in the commentaries to the competitions or in historical newspapers. We are able to geolocate 306 out of 309 machines precisely. Because all firms operate in urban areas, we calculate machine adoption in all parishes located within 50 km from these cities: a reasonable indicator of the amount of early adoption these firms were exposed to. Similarly, for this database we calculate covariates based on the characteristics of all parishes within 50 km from where these producers operated.

A.2 Variable description

Recruitment. We take recruitment from two sources. British Army recruits come from Floud et al. (1990), who digitized the original muster rolls of 23,749 soldiers who served in the Army between 1790 and 1819. From the original regimental books, he selected at random recruits joining the Army in each of the three decades until he reached a pre-established quota. For each soldier sampled, he digitized demographic and anthropometric information: we use the (standardized) birthplace to locate these men on the map of Southall and Burton (2004). Out of the 23,749 soldiers in Floud et al. (1990), we are able to geolocate 15,187 (64%).

Royal Navy recruits come from the original muster rolls of 262 ships in commission between 1793 and 1815. Our data combine digitization of three complementary and non-overlapping sources. First, the Battle of Trafalgar project digitized records of 18,101 sailors on board the 33 ships who fought at Trafalgar with Nelson.[25] Second, Dancy (2012) collected additional records for 42,204 men sailing on 134 different ships sampled randomly to be representative across the size distribution of Royal Navy vessels.[26] Third, we digitized records from 34,707 sailors on board of 95 additional ships. We draw a random sample of ships from Colledge (1969) making sure that the new ships did not appear in the other two sources.[27] For each of the selected ships, we collect information on ship characteristics from *Three Decks* and on every sailor on board from the muster rolls, which were compiled every two month by the pursers. We observe each of our 262 ships at one point in time between 1793 and 1815: for that period we take information of everyone on board. We have data for 95,014 men of which we can geolocate 30,330 (32%) on the map of Southall and Burton (2004).

From recruitment data we construct six variables. *Total recruits per 1,000 people* is the sum of British Army soldier and Royal Navy sailors per 1,000 people (as counted in the 1801 Population Census: variable *TOT_POP* in Southall et al., 2020). Similarly, *Royal Navy recruits per 1,000 people* and *British Army recruits per 1,000 people* are Royal Navy sailors and British Army soldiers per 1,000 people. *Royal Navy recruits on shallow ships per 1,000 people* is Royal Navy sailors with fewer than three years of sea experience (landsmen and ordinary seamen) sailing on ships with depth of hold shallower than 5m, divided by 1,000 people. *Royal Navy recruits on deep ships per 1,000 people* is Royal Navy sailors with fewer than three years of sea experience (landsmen and ordinary seamen) sailing on ships with holds deeper than 5m, divided by 1,000 people. *Total recruits per 1,000 men* is the sum of British Army soldier and Royal Navy sailors per 1,000 men (as counted in the 1801 Population Census: variable *MA_1801* in Southall et al. (2020). *Royal Navy recruits*

[25] See https://www.nationalarchives.gov.uk/nelson/.

[26] Prof. Dancy collected these records for two separate projects. The first 81 ships come from Dancy (2012) and contain musters for a random sample of ships commissioned between 1793 and 1801 across three commissioning dockyards (Chatham, Portsmouth and Plymouth). The other 53 ships are from Dancy (2018), and are sampled at random in each odd year between 1803 and 1815. We thank prof. Dancy for sharing his data with us.

[27] We generate a random page number and a random month in the period 1800–15. We find the ship listed in Colledge closest to that page which satisfies: i) has at least 13 guns; ii) is not already sampled (not in prof. Dancy data nor at Trafalgar); and, iii) has a muster record at the National Archives available close to that date.

per 1,000 men is Royal Navy sailors per 1,000 men. We transform each of these six variables with the natural logarithm, and model the extensive margin explicitly by assigning -1 to all cells with no recruitment (Chen and Roth, 2023).

Agricultural machines. Labor-saving and non-labor saving machines extend the dataset in Caprettini and Voth (2020). We assemble a list of agricultural machines in use at the time of the Napoleonic Wars from two sources: farm advertisements in British newspapers and the *General Views of Agriculture*. We collect newspaper advertisements from British Library and Findmypast (2022). Within the universe of all articles of the 60 regional newspapers active between 1750 and 1830 and present in the corpus, we perform two sets of searches: first, for the following exact strings: 'threshing machine,' 'reaping machine,' 'mowing machine,' 'horse rake,' 'horse hoe,' 'chaffing machine,' 'turnip cutter,' 'cake crusher'. Second, we search for the following exact strings: "farm auction," "farm sale," "farm for sale," "farm to be let," "farm to be sold," and "farm to sell."[28] We restrict our search to articles classified as either 'advertisement' or 'classifieds.' Next, we read in full each article retrieved: humans read all articles mentioning at least one machine. We ask OpenAI to read the (many more) articles advertising farm sales/leases. We use all information from any article that advertises the sale or the lease of one of these machines or of a farm that lists them among its assets. We drop all advertisements of producers that only provide information about the location of the machine factory, usually an industrial town. We also only consider ads for a single machine whenever we find the same advertisement printed more than once. We manually geolocate the machines in each advertisement, based on the map prepared by Southall and Burton (2004).

We complement advertisement data with that in the *General Views of Agriculture* published between 1793 and 1815. Each volume of the *Views* devotes one chapter to the "Implements of Agriculture" of a different county and contains detailed reports on farms visited, their owners and the agricultural machines found on the premises. We locate on the map of Southall and Burton (2004) any farm which reports one of the machines we searched in the newspapers. In addition, we collect information on

[28]We collected ads for threshing machines in the spring of 2016 and for other machines and farms for sale/lease in the fall of 2019.

'rollers,' 'winnowing machines' and 'reaping machines.' We ensure that we do not double count any machine from the newspapers, comparing the names of the owners in the two sources.

From the full list of machines, we create two variables. *Labor-saving machines* is the sum of threshers, horse rakes, horse hoes, mowing machines, rollers, winnowing machines and reapers: we have 3,878 of these machines. *Non-labor saving machines* is the sum of chaffing machines, turnip cutters and cake crushers: we observe 997 of them. We classify the machines following the historical literature (Rahm, 1844; Fussell, 1952; Walton, 1973).

Farm ads. We search for articles advertising the sale or lease of a farm on the newspapers digitized by British Library and Findmypast (2022). Within the universe of all articles of the 60 regional newspapers active between 1800 and 1830 and present in the corpus, we search for the following exact strings: "farm auction," "farm sale," "farm for sale," "farm to be let," "farm to be sold," and "farm to sell."[29] We restrict our search to articles classified as either 'advertisement' or 'classifieds.' Next, we ask OpenAI to identify relevant articles inside the page retrieved (there are often more than one relevant advertisement in any given page) and determine the location of the farm by providing a parish and a county in Britain. We geolocate these places with OpenStreetMap and count the number of advertisement assigned inside every cell. In the regressions, we use the natural logarithm of farm ads, and model the extensive margin explicitly by assigning -1 to all cells with no ads (Chen and Roth, 2023).

Mechanical apprentices. We use the Apprenticeship Books or the Board of Stamps to compile a list of apprentices who trained between 1710 and 1791 to become metal workers or watchmakers. During the 18$^{\text{th}}$ century, master craftsmen were allowed to indenture an apprentice for seven years after payment of a duty. We use commercial Optical Character Recognition software (*Transkribus*) to digitize the handwritten records of 63,446 duties paid between 1710 and 1791. We automatically extract the residence and occupation of the master and use it to create a cell-level variable equal to the number of apprentices trained to become metal workers (mostly

[29]We performed these searches in the fall of 2019.

wheelwrights, millwrights and blacksmiths) and watchmakers. We can geolocate a total of 5,308 metal workers and 568 watchmakers and use them to classify cells into one of three categories (none / one / more than one apprentice).

Distance to coast and deep sea. EMODnet Bathymetry Consortium (2018) provides bathymetric survey data on a grid of 0.0625 × 0.0625 arc minutes. We use the grid to construct barymetric profiles of the seabed in front of Great Britain for depth from 0 to 25 meters deep, in 5-meter steps. Distance to the coast is the distance of each hexagonal cell centroid to the closest point on the 0 meter deep profile. Distance to deep sea, our instrument, is the distance of each hexagonal cell centroid to the closest point on the 15 meter deep profile. The distances to the other depths (5, 10, 20 and 25 meter deep) are constructed similarly.

1801 population. Parish population comes from the Population Census of 1801 Southall et al. (2020). The original variables is *POP_1801*. We merge the Census to the historical map of English and Welsh parishes with ancient county (*ANC_CNTY*) and parish (*ANC_PAR*), before taking these data to our map of hexagonal cells. We transform the variable with the natural logarithm.

1801 sectoral shares. We construct sectoral shares from the Population Census of 1801 (Southall et al., 2020). We calculate two shares: for agriculture and trade. In 1801 these shares reflect the number of workers employed in the two sectors (variables *OC_AGRIC* and *OC_TRADE*) divided by the total number of workers (which also include people employed in the residual category "other": *OC_OTHER*). We merge the Census to the historical map of English and Welsh parishes as we do with the population.

Gender ratios (1801 and 1811). We compute the gender ratio using data from the Population Censuses of England, 1801 and 1811 (Southall et al., 2020). The variable is equal to the total number of women (variable *FE_1801* in 1801, *TOT_FEM* in 1811) divided by the total number of men (variable *MA_1801* in 1801, *TOT_MALE* in the other years). We merge the Census to the historical map of English and Welsh parishes as we do with the population. We transform the variable with the natural logarithm.

Area. The total land area of the cell (in square km) is calculated with ArcGIS based on the grid described in the previous section. We transform the variable with the natural logarithm.

1801 density. Density is 1801 population divided by the area of the cell (Southall et al., 2020). We transform the variable with the natural logarithm.

Potential yield of wheat. We take the potential yield of wheat from the Food and Agriculture Organization Global Agro-Ecological Zones database (FAO-GAEZ). We use the potential yield for summer wheat with intermediate inputs and rain-fed irrigation. The original data is a raster that covers the entire land mass of the Earth on a grid of about 9.25 × 9.25 km. We first resample the raster on a finer grid of 8 × 8 meters with the "nearest" method. Next, we superimpose the map of hexagonal cells described in the previous section and for every cell of the wheat raster we take its centroid and assign it to the hexagonal cell where the centroid falls. Finally, for every cell we take the average potential yield of all the raster cells that fall inside the hexagon cell.

Ruggedness. We calculate ruggedness with data from Nunn and Puga (2012). Raw data is defined on a grid of 30-arc seconds: for every cell, it records the change in elevation relative to surrounding cells: $\sqrt{\sum_{i=r-1}^{r+1} \sum_{j=c-1}^{c+1} (e_{ij} - e_{rc})^2}$, with e_{rc} elevation in the cell on row r, column c. We superimpose the ruggedness grid to our hexagonal grid and take the weighted average ruggedness in our hexagons, with weights defined by the size of the ruggedness cells. As suggested by Nunn and Puga (2012) we divide ruggedness by 100,000, so that it is measured in hundreds of meters.

Bounty of the sea index. We calculate the bounty of the sea index with the method of Dalgaard et al. (2020) and data from Food and Agriculture Organization (2016) and Kaschner et al. (2013) which record country-level information on fish catch and a probability of finding different species of fish on a grid covering the seas. We use the FAO Fisheries Yearbook to identify the top eight fish caught by English boats in 1950-59 (the earliest decade available): these are the Atlantic cod, the Atlantic herring, the Haddock, the Whiting, the Pollock, the European plaice, the European hake and the Picked dogfish and account for 83% of the catch by live weight.[30] Next, we construct 0.1°× 0.1°buffers adound our hexagonal cells: this

[30]We drop two acquatic species belonging to the top ten of British fish but not covered by

allows to define area just outside each cell that may be covering fisheries. We then use Aquamaps data to compute the average probability of finding each of the eight species of fish inside the buffer of each hexagonal cell. Our bounty of the sea index is the simple average of the eight probabilities.

Country banks in 1791. The locations of country banks (private banking institutions outside of London) is extracted from Dawes and Ward-Perkins (2000), which contains all country banks over 1688—1953. We only consider banks that were active as of 1791. Since the country banks were limited in size (by restrictions on the number of partners) these were generally unit banks, lending credence to their single-town locations.

Distance to 1791 postal town. A post town is a formal part of the state communication system, those towns at which horses are changed at points spread somewhat equidistantly along straight routes. Robertson (1961) documents the universe of post towns at 1791. We transform the variable with the natural logarithm.

Distance to newspapers. We first determine which of the newspapers in British Newspaper Archive was in print before 1830. Next, we manually geolocate the cities in which these newspapers were printed. Finally, we calculate the straight-line distance of the centroid of every hexagonal cell to each of these towns. We keep only the distance to the closest town with a newspaper. We transform the variable with the natural logarithm.

1706-91 steam engine dummy. Kanefsky and Robey (1980) compiled a comprehensive list of all the early steam engines in use in England since 1706 (mostly Newcomen engines): we geolocate the engines installed before 1792 on the map of Southall and Burton (2004). We then take this map to the grid of hexagonal cells and create an indicator equal to one in cells with at least one engine.

1700-90 patent dummy. Woodcroft (1854) collects the population of all British patents granted between 1617 and 1854. We collect the residence of every inventor who filed a patent between 1700 and 1790 and geolocate on the map of England (Southall and Burton, 2004). We then take this map to the grid of hexagonal cells and create an indicator equal to one in cells home to at least one inventor.

Aquamaps: seaweeds and rays.

Royal Navy port. We compile a list of all known ports or anchorages of the Royal Navy prior to 1815 from two sources. The first is the *Universal British Directory* of 1791 (Barfoot and Wilkes), which contains topographical information of all British population centers at the start of the Wars against France. The second is *Three Decks*, a website collating naval history research of enthusiasts and scholars.[31] We assign a cell to a Royal Navy port or anchorage if a parish within 8 km from the cell centroid is named in one of the two sources.

Commercial port. We compile a database of major commercial ports from Alvarez-Palau et al. (2019). The raw data contains a list of 479 historic ports and landing areas along the coasts of England and Wales. We assign a cell to a commercial port if there exists a port within 8 km from its centroid, if the cell does not have a Royal Navy port and if it has a population density of at least 30 people per square meter. The density condition excludes 92 minor locations with 1801 population as low as two people.

RASE Entries. We collect the number of steam-powered threshers presented at one of the competitions held by the Royal Agricultural Society of England from the first volumes of the *Journal of Agricultural Society of England*. Between 1841 and 1872, there were twelve competitions for the best threshing machine, to which 309 separate machines took part. We collect information on the producers of each of these machines from the competition records described in the *Journal*. In all, we are able to geolocate 306 machines on the map of England (Southall and Burton, 2004).

RASE Productivity. We calculate the productivity of the machines presented at the RASE competitions from the records published on volumes of the *Journal of Agricultural Society of England*. For each competition, the *Journal* reports detailed information on the outcome of the standardized trials used to judge these machines. We harmonize productivity to measure output in sheaves per hour per man and include in all regressions competition fixed effects to account for differences in judges or trials over the years.

[31] See https://threedecks.org/.

B Robustness Checks

B.1 Extensive margin and discrete choice models

Our dependent variable, machine adoption, has many zeros and is skewed. We first focus on the extensive margin – using a dummy for whether machine adoption happened at all – and estimate probit and logit regressions. The first two columns of Appendix Table A.9 report the simple linear probability model, with and without region fixed effects. Recruitment predicts the adoption dummy with OLS. The rest of the table shows that recruitment strongly predicts labor-saving machine adoption with both probit (cols 3–4) and logit (cols 5–6): results remain strong across specifications, and the marginal effect estimated at the mean of the recruitment distribution is close to the estimate of the linear probability model.

Second, we use discrete choice models for count variables. Because the variance of our dependent variable is 5.6 times larger than the mean (8.4 vs 1.5), Poisson regressions are not appropriate and we focus on the negative binomial. The first two columns of Table A.10 show the baseline OLS results. The other columns report the negative binomial regressions, which confirm a strong positive relation between recruitment and machine adoption, effects are near-identical to OLS.

B.2 Matching exercises

Matching methods offer an alternative way to identify causal effects. Figure A.8 presents results from CEM, entropy balancing and Table A.13 estimates with nearest neighbour matching. We define "treated" units as those with recruitment above the sample median. Black coefficients show that these areas had significantly more machines (Panel A). CEM restricts the sample to strata with both treated and controls, ensuring balance while minimizing sample loss (Iacus et al., 2012). Light and dark red coefficients indicate that effect of recruitment on adoption is unaffected. R^2 are 3-4 times larger, but effects remain strong. Figure A.8 also reports in blue entropy balancing estimates (Hainmueller, 2012). This method keeps the full sample but re-weights observations to ensure balance across treated and controls. This leads to larger effect of recruitment on adoption. Finally, Appendix Table A.13 shows nearest neighbour matching estimates, where we restrict the sample to observations that are close in terms of geography, population, agricultural share, wheat suitability and number of farm ads. We match each high-recruitment cell to one, three and five similar cells with low recruitment (cols 1-3) overall or in the same region (cols 4-6). Estimates are significant and close to baseline results.

B.3 Spatial standard errors

Spatial correlation can lead to understated standard errors. Figure 1–Panels E–F display spatial dependence in our dependent variables. Table A.11 displays Moran's I p-values, which suggests spatial correlation disappears beyond 600 km in all specifications. To parametrically correct standard errors, we apply the Conley (1999) formula. Table A.12 shows corrections when spatial correlation is assumed to disappear after 50, 100, 200, 400 and 600 km, as well as county-level clustering. Standard errors initially rise, yet results remain strong in all specifications; assuming spatial dependency over longer distances increases significance. Neither recruitment coefficient falls below 1% significance; the strength of our results is not impacted by spatial errors.

B.4 Plausibly exogenous

Are IV estimates robust to small violations of the exclusion restriction? Distance to deep sea is uncorrelated with pre-war characteristics and doesn't predict maritime trade, army recruitment nor farm ads, broadly supporting the exclusion restriction. In this section we also present the results of the test of Conley et al. (2012), which identifies confidence bounds of the IV estimates when the exclusion restriction is violated. Figure A.9 report these bounds on the y-axis, against the assumed violation on the x-axis (i.e. the assumed direct effect of distance to the deep sea on adoption). Panel A shows the specification with all controls and Panel B adds region fixed effects. We indicate the reduced form coefficient as a vertical line for reference. In both specifications, the direct effect must account for more than half of the reduced form coefficient for the IV to become insignificant. Such large direct effects of deep sea on adoption appear unlikely.

B.5 Alternative samples, recruitment definition, and machine classification

Results are robust in several alternative samples. First, using newspapers can create challenges (Beach and Hanlon, 2022). Our main analysis in Table 1 excludes urban areas - where farm implements are unlikely to be used - but it includes all cells within 50 km from a newspaper, regardless of whether they had farms for sale or lease. Neither of these choices is crucial. Including urban cells does not affect our results (Table A.14), nor does excluding cells never mentioned in farm ads (Table A.15).

Second, locations close to supply yards and those in Wales may bias results in our favor. Nineteen victualling yards supplied the British armed forces with food and other provisions. High demand for foodstuffs there may have promoted technological progress, confounding our estimates. Second, remote and sparsely populated areas (such as most of Wales) saw barely any recruitment. Land was often unsuitable for cereals; accordingly, there was little incentive to adopt threshers and other labor-saving machines. Including both areas may bias results in our favor but in practice neither of them drives our conclusions. Table A.16 drops 59 cells within 8 km from one of the victualling centers and Table A.17 excludes Wales: our results hold.

Third, our IV strategy defines the coastal sample as cells within 15 km from the coast, capturing half a day's walking distance. Figure A.10 shows that IV and reduced from results are robust to different cut-offs, and that the point estimates are stable. Our choices for constructing samples do not appear to affect our conclusions.

Fourth, we experiment with variations in our measure of military recruitment. We start in Appendix Table A.18 where we re-scale recruitment by 1801 male population.[32] Results remain significant in OLS and IV models. We also consider different transformations of recruitment per capita. The distribution of this variable has a high skew (44.8) and a large proportion of zeros (45%). In our baseline results we follow Chen and Roth (2023), take the natural logarithm and model the extensive margin explicitly, assigning -2 to cells with zero recruitment. This insures cells with

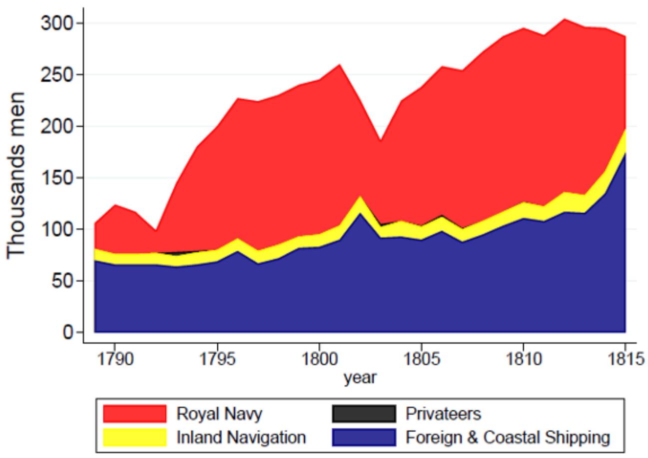
[32] We cannot normalize by *working-age* men as age was not recorded until the 1851 Census.

no recruitment receive the lowest value. Moreover, when recruitment is the dependent variable, as in the first stage regressions, it implies that the extensive margin is valued at 200 log points. This choice is arbitrary but inconsequential: Appendix Tables A.19 and A.20 show that all results survive when we assign -1 or -3 to cells with no recruitment.

Finally, our labor-saving machinery classification may introduce errors. We re-estimate with threshers only (Table A.21) since they are unlikely to be underreported and clearly saved labor. Results are near-identical, confirming a significant impact of war-induced labor shortages on thresher adoption, the most important rural technology of the time.

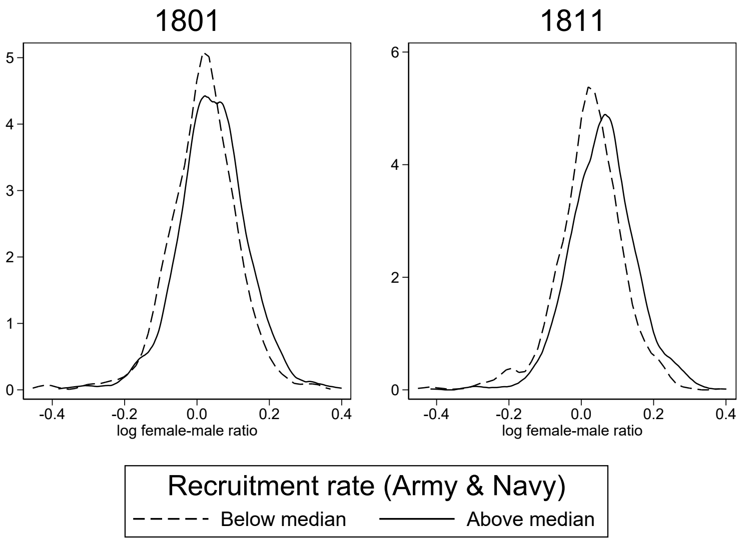
C Appendix figures

Figure A.1: British men employed at sea: 1790-1815.



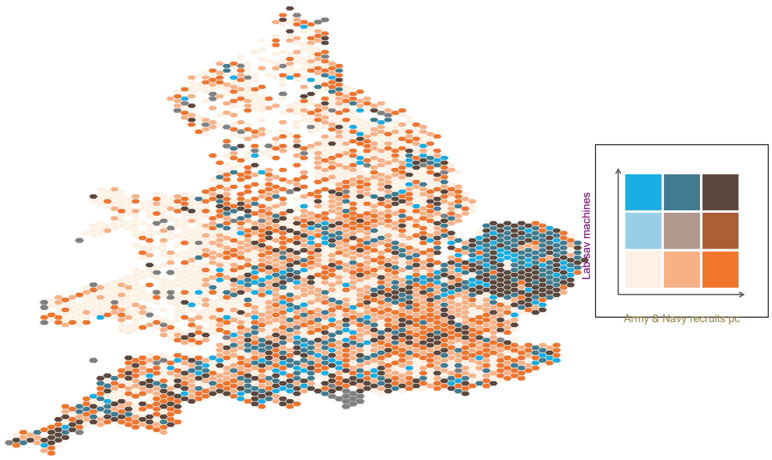
Notes: Source: Dancy (2012), Figure 2.1.

Figure A.2: Sex Ratios and Recruitment



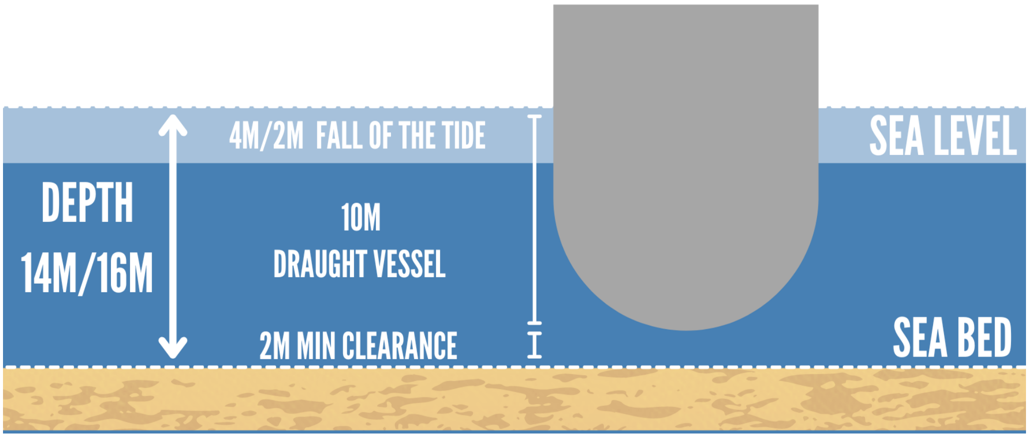
Notes: Kernel distribution of log female-male ratios in 1801 (left) and 1811 (right). Dashed lines: cells below median military recruits (Army and Navy) per capita; solid lines: cells above median recruits per capita. Kernel: Epanechnikov, bandwidth: 0.01.

Figure A.3: Machine adoption and military recruitment (Bicolor Map)



Notes: Military recruitment (Army and Navy) and machine adoption. Darker blue cells have greater adoption, darker red cells have greater total recruitment.

Figure A.4: Depth requirement for safe anchorage.

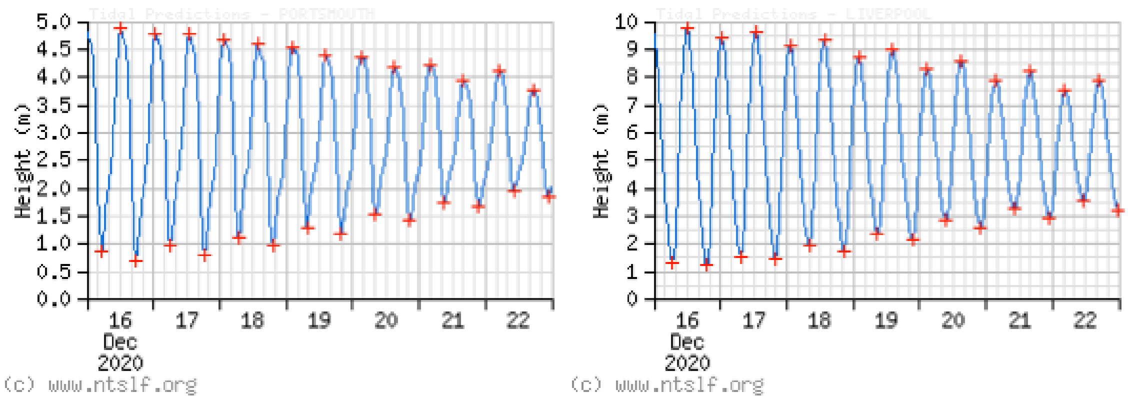


Notes: Illustration of the FUD rule. Source: http://www.sailtrain.co.uk/navigation/theightanchoring.html

Figure A.5: Tides in Portsmouth and Liverpool

A. Portsmouth

B. Liverpool

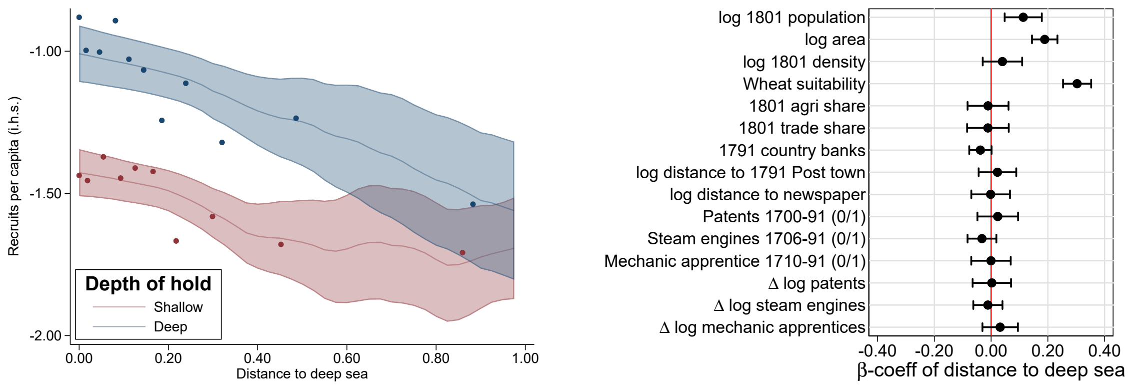


Notes: Tidal variation in the sea level over the week of 16 December 2020 in two British ports. Panel A: Portsmouth. Panel B: Liverpool.

Figure A.6: IV strategy validation

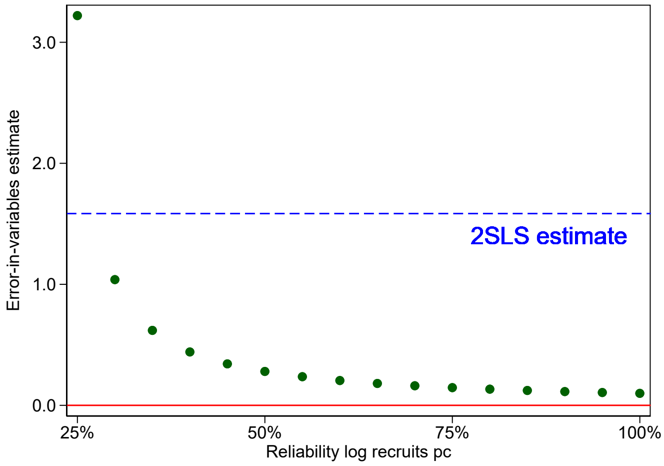
A. Depth of hold of recruits' ships

B. Balance of the instrument



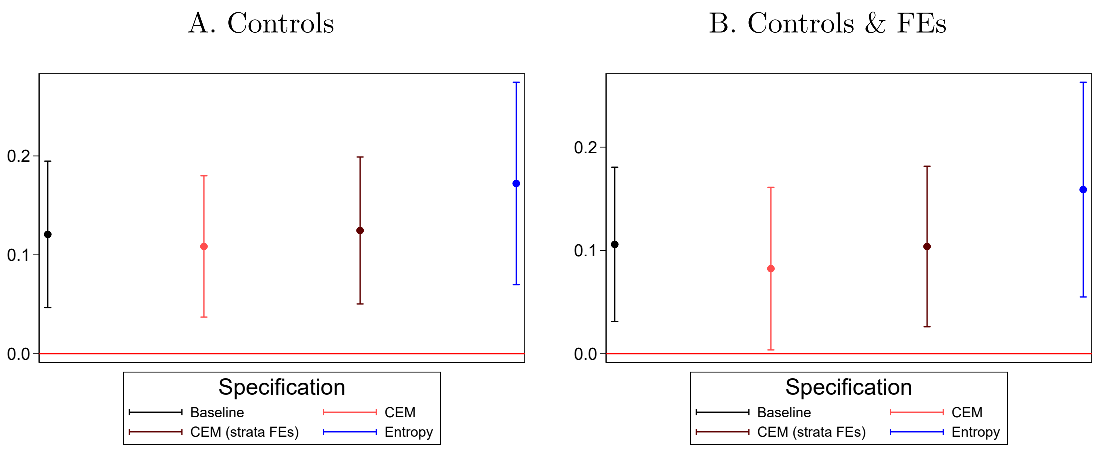
Notes: The sample consists 886 cells within 15 km from the coast. Panel A: distance to deep sea and depth of Navy recruits' ships. We use Cattaneo et al. (2024) Stata package `binsreg` to plot unconditional binscatters of distance to the deep sea (x-axis) on log Royal Navy recruits per capita (y-axis). We split recruits into those found on deep (>5m depth of hold) ships (in blue) and those sailing on shallow (<5m) ships (red). We superimpose kernel-weighted local polynomial smoothing lines and their 95% confidence intervals. Panel B: we report the coefficients of separate regressions of the variables listed on the left on distance to deep sea. We control for distance to coast in each regression. We use robust standard errors to draw 95% confidence intervals around estimates.

Figure A.7: Error in variables estimates



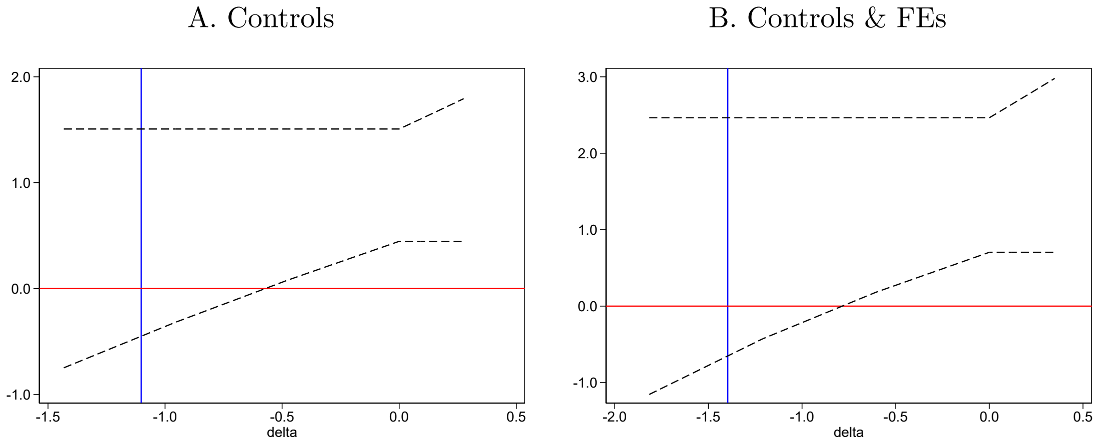
Notes: Error in variable estimates. The figure plots OLS estimates of the impact of naval recruitment on labor saving machine adoption (y-axis) against different levels of assumed reliability of the naval recruitment variable. The point at 100% reliability corresponds to the baseline OLS estimates, which assume no measurement error in recruitment. The dashed, horizontal blue line corresponds to the IV estimates. The sample consists 886 cells within 15 km from the coast.

Figure A.8: Matching exercises



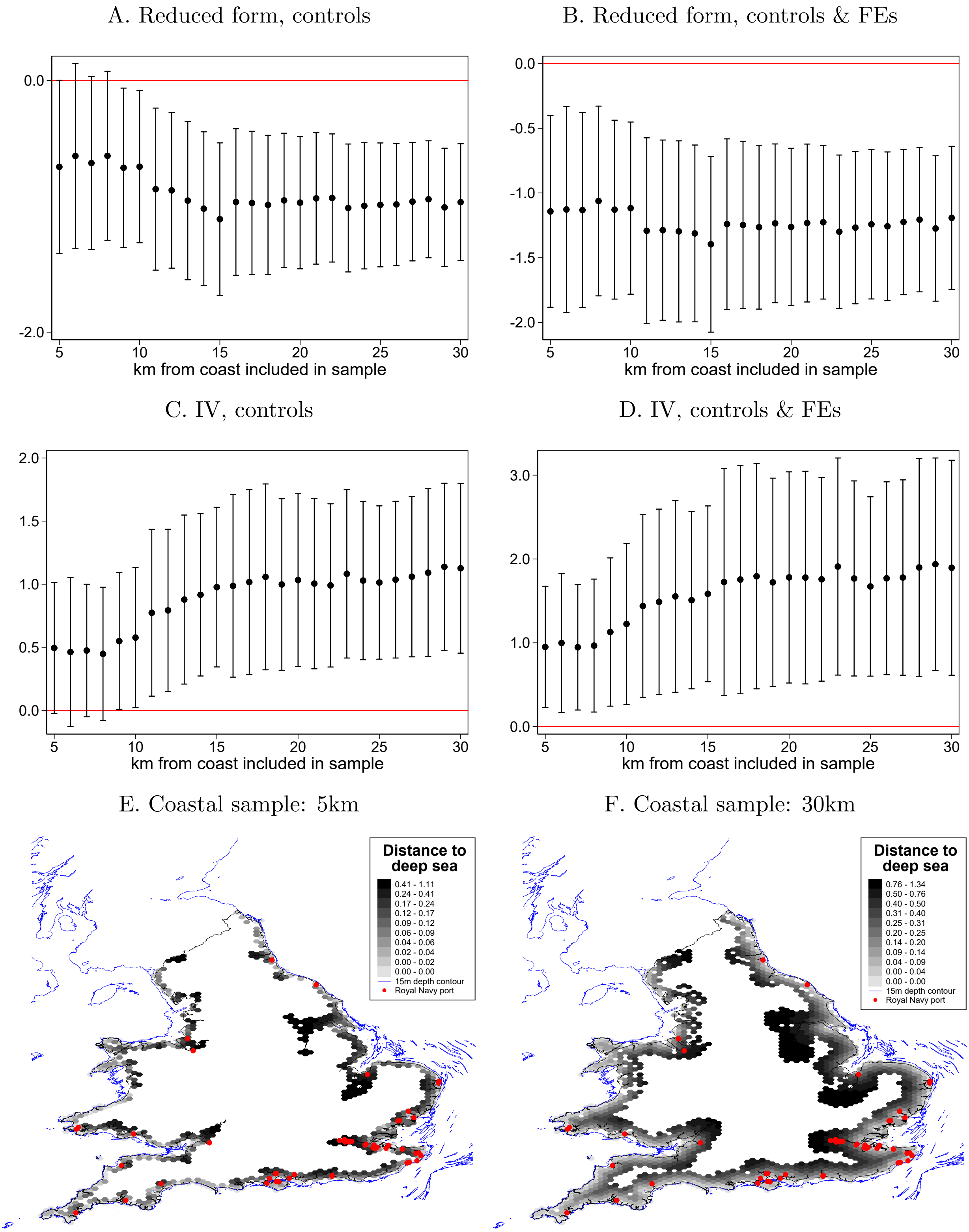
Notes: Coefficients and 95% confidence intervals of the effect of total military recruitment on labor saving machine adoption with different estimation methods. In each panel, from left to right, estimation method is: OLS (baseline); Coarsened Exact Matching (CEM: Iacus et al., 2012); CEM with strata fixed effects; weighted OLS with entropy weights (Hainmueller, 2012). Panel A: specifications with all control. Panel B: specifications with controls and five region fixed effects. See Section B.2 for details.

Figure A.9: Plausibly exogenous



Notes: Effect of violation of exclusion restriction (Conley et al., 2012). Union of 90% confidence intervals of the IV estimates (y-axis) when the exclusion restriction is violated (x-axis). Blue vertical lines: point estimate of the reduced form coefficients. Panel A: specifications with all control. Panel B: specifications with controls and five region fixed effects. See Section B.4 for details.

Figure A.10: Alternative definitions of coastal sample



Notes: Robustness to the definition of coastal sample. Panels A–B: reduced form: effect of distance to deep sea on labor saving machine adoption in different coastal samples. Panels C–D: IV estimates: effect of naval recruitment on labor saving machine adoption in different coastal samples; instrument is distance to the deep sea. Panels A and C: specifications include distance to the coast and all controls; Panels B and D: specifications include distance to the coast, all controls and five region fixed effects. We use robust standard errors to draw 95% confidence intervals around point estimates. Panels E–F: value of instrument in samples of cells within 5 km and 30 km from the coast.

D Appendix tables

Table A.1: Gender imbalances and recruitment

	log female - male ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
	1801	1801	1801	1811	1811	1811
log total recruits p.c.	0.010***	0.005***	0.006***	0.015***	0.009***	0.010***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Full controls	No	Yes	Yes	No	Yes	Yes
Region FEs (5)	No	No	Yes	No	No	Yes
R^2	0.021	0.118	0.142	0.056	0.138	0.158
Mean dep var	0.031	0.031	0.031	0.041	0.041	0.041
Observations	2603	2603	2603	2473	2473	2473

Notes: OLS estimates. Dependent variable is the log of female-male ratios. Cols 1–3: gender ratio in 1801. Cols 4–6: gender ratio is in 1811. Units of observation are 2603 equally sized hexagonal cells. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.2: Validation. Distance to deep sea and port presence.

	Port		Distance to port	
	(1)	(2)	(3)	(4)
	Royal Navy	Commercial	Royal Navy	Commercial
Distance to deep sea	-0.091***	-0.026	0.071***	0.028
	[0.029]	[0.078]	[9.400]	[7.701]
Distance to coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
R^2	0.209	0.305	0.857	0.320
Mean dep. var.	0.095	0.460	139.053	78.179
Observations	886	886	886	886

Notes: β-coefficients from OLS estimates. Dependent variables are: Cols 1-2: an indicator for port presence within 8 Km from the cell centroid; Cols 3-4: distance to the closest of the busiest 15 ports in England. Cols 1 and 3: ports are used by Royal Navy ships. Cols 2 and 4: ports are used by commercial ships. Units of observation are 886 equally sized hexagonal cells lying within 15 Km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.3: Validation. Distance to deep sea and recruitment by depth of ship's hold.

	log recruits p.c.			
	(1) Shallow hold	(2) Deep hold	(3) Shallow hold	(4) Deep hold
Distance to deep sea	-0.280**	-0.601***	-0.285**	-0.470***
	[0.127]	[0.159]	[0.134]	[0.173]
R^2	0.177	0.206	0.182	0.229
Mean. dep. var.	-1.518	-1.118	-1.518	-1.118
Distance to coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	Yes	Yes
p-value deep = shallow		0.023		0.242
Observations	886	886	886	886

Notes: OLS estimates. Dependent variable Royal Navy recruits per capita (i.h.s.). Cols 1–2: recruits sailing on ships with shallow draught (less than 5m). Cols 3–4: recruits sailing on ships with deep draught (more than 5m). Units of observation are 886 equally sized hexagonal cells lying within 15 Km from the coast. The p-value at the bottom of the table tests that the coefficient of distance to deep sea in cols 1-3 and 2-4 are the same. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Never-takers

	Labor saving machines		
	(1) Coastal sample	(2) Never takers	(3) Rest
Distance to deep sea	-1.397***	-0.179	-1.453***
	[0.347]	[0.533]	[0.367]
R^2	0.300	0.518	0.298
Mean. dep. var.	1.442	0.159	1.510
Distance to coast	Yes	Yes	Yes
Full controls	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes
Observations	886	44	842

Notes: Reduced form estimates for coastal sample (col 1), for the sample of cells with no Royal Navy recruits within 8Km (col 2), and for the rest of the sample (col 3). Sample in col 1 consists of 886 cells within 15 km from the coast. All regressions include the full set of controls and five region fixed effects. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Analysis of compliers

	Average				p-value	
	Coastal Sample (1)	Compliers (2)	Always Takers (3)	Never Takers (4)	(2) - (3)	(2) - (4)
Distance to coast	0.040	0.050	0.059	0.017	0.526	0.004
	(0.002)	(0.011)	(0.004)	(0.002)		
log 1801 population	7.187	7.369	7.529	6.763	0.406	0.002
	(0.029)	(0.158)	(0.058)	(0.075)		
log area	4.630	4.782	4.749	4.444	0.706	0.002
	(0.011)	(0.081)	(0.009)	(0.037)		
Wheat suitability	3747.462	3814.310	3848.155	3616.899	0.680	0.036
	(13.072)	(81.416)	(20.268)	(31.507)		
1801 % agri workers	0.353	0.297	0.318	0.413	0.686	0.012
	(0.007)	(0.041)	(0.013)	(0.017)		
1801 % trade workers	0.109	0.103	0.126	0.094	0.306	0.698
	(0.003)	(0.019)	(0.008)	(0.009)		
1801 % trade workers	2.928	2.940	2.723	3.129	0.152	0.170
	(0.020)	(0.123)	(0.048)	(0.040)		
1801 % trade workers	3.686	3.775	3.571	3.763	0.138	0.928
	(0.021)	(0.116)	(0.045)	(0.040)		
1791 country banks	0.334	0.222	0.519	0.198	0.168	0.904
	(0.027)	(0.165)	(0.079)	(0.040)		
1707-90 steam engines (0/1)	0.056	0.013	0.061	0.071	0.350	0.296
	(0.008)	(0.046)	(0.017)	(0.020)		
1700-90 patents (0/1)	0.067	-0.032	0.127	0.049	0.016	0.138
	(0.008)	(0.053)	(0.024)	(0.016)		
1710-92 mechanic apprentice (0/1)	0.396	0.378	0.552	0.247	0.130	0.236
	(0.017)	(0.095)	(0.035)	(0.032)		
log army recruits pc	-0.943	-1.045	-0.472	-1.372	0.060	0.262
	(0.048)	(0.260)	(0.105)	(0.084)		
Proportions	1.00	0.181	0.409	0.410		
		(0.032)	(0.023)	(0.023)		

Notes: Average characteristics in the coastal sample (col 1) and in the sample of compliers (col 2), always takers (col 3) and never takers (col 4). We apply the method of Marbach and Hangartner (2020) to profile compliers and discretize naval recruitment and distance to the deep sea by splitting the sample at the median. The last two columns report p-values for the test that the average of compliers are similar to always takers and to never takers.

Table A.6: Adoption: Synergies between labor scarcity and other drivers of growth. Dependent variable is labor saving machines

	Labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
Tot recruits pc × growth driver		-0.170***		0.399***		-0.020
		[0.062]		[0.142]		[0.079]
log total recruits p.c.	0.106***	0.146***	0.104***	0.036	0.101***	0.110**
	[0.038]	[0.048]	[0.038]	[0.035]	[0.038]	[0.052]
Growth driver	-0.026	-0.054	0.278*	0.151	-0.654***	-0.650***
	[0.095]	[0.097]	[0.149]	[0.140]	[0.142]	[0.136]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.287	0.289	0.287	0.293	0.296	0.296
Mean. dep. var.	1.490	1.490	1.490	1.490	1.490	1.490
Growth driver:	Coal deposit	Coal deposit	1791 Banks	1791 Banks	Slave port	Slave port
Observations	2603	2603	2603	2603	2603	2603

Notes: OLS estimates. Dependent variable is labor saving machines. The table explores interactions of labor scarcity with other important determinants of British growth. Cols 1-2: growth factor is coal presence. Cols 3-4: growth factor is country banks. Cols 5-6: growth factor is slave ports. Units of observation are 2603 equally sized hexagonal cells. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: The role of commercial ports: Reduced form and IV controlling for distance to commercial port

	Machines			
	(1) Lab sav	(2) Lab sav	(3) Non lab sav	(4) Non lab sav
Distance to deep sea	-1.397***	-0.776***	-0.156	-0.169
	[0.347]	[0.298]	[0.143]	[0.144]
Distance to commercial port		0.007***		0.002***
		[0.001]		[0.001]
R^2	0.300	0.238	0.133	0.142
Mean. dep. var.	1.442	1.442	0.342	0.342
Distance to the coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
Observations	886	886	886	886

	Machines			
	(1) Lab sav	(2) Lab sav	(3) Non lab sav	(4) Non lab sav
log Royal Navy recruits p.c.	1.585***	1.656***	0.177	0.196
	[0.535]	[0.567]	[0.167]	[0.173]
Distance to commercial port		0.010***		0.003***
		[0.003]		[0.001]
R^2	-0.261	-0.285	0.082	0.085
Mean. dep. var.	1.442	1.442	0.342	0.342
Distance to the coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
Observations	886	886	886	886

Notes: Sample consists of 886 cells within 15 km from the coast. A 'commercial port' is one where ship traffic comprises less than 25% Royal Navy, based on analysis of Lloyds List for 1799-1800. Panels A and B: Dep. var. is labor-saving machines (cols 1–2) and non-labor saving machines (cols 3–4). Units of observation are 886 equally sized hexagonal cells within 15 km from the coast. Robust s.e. in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: The role of land market: Reduced form and IV with farm ads

	log farm ads		Farm ads 0/1	
	(1) RF	(2) IV	(3) RF	(4) IV
log Royal Navy recruits p.c.		-0.048		-0.075
		[0.180]		[0.058]
Distance to deep sea	0.042		0.066	
	[0.158]		[0.046]	
R^2	0.453	0.440	0.230	0.067
Mean. dep. var.	1.309	1.309	0.885	0.885
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
Observations	886	886	886	886

Notes: Dep. var.: log farm ads. We follow Chen and Roth (2023) and model explicitly the extensive margin: cells with no farm ads are assigned -1 (col 1 and 3) and -2 (col 2 and 4). All columns include the full set of controls and five region fixed effects. Units of observation are 886 equally sized hexagonal cells within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Extensive margin: linear probability model, probit and logit.

	Labor saving machines (0/1)					
	(1) LPM	(2) LPM	(3) Probit	(4) Probit	(5) Logit	(6) Logit
main						
log total recruits p.c.	0.021***	0.017***	0.085***	0.072***	0.143***	0.122***
	[0.006]	[0.006]	[0.021]	[0.021]	[0.036]	[0.037]
R^2	0.320	0.332				
Mean. dep. var.	0.450	0.450	0.450	0.450	0.450	0.450
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	No	No	No
Marginal effect at mean recruitment			0.024***	0.020***	0.024***	0.020***
			(0.006)	(0.006)	(0.006)	(0.006)
Observations	2603	2603	2603	2603	2603	2603

Notes: Estimates of Equation (1). Dep. var.: dummy for at least one labor saving machine. Cols 1–2: OLS (linear probability model). Cols 3–4: probit. Cols 5–6: logit. Cols 3–6: marginal effect calculated at the mean value of total recruitment. Units of observation are 2603 equally sized hexagonal cells. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: Discrete choice model: negative binomial.

	Labor saving machines			
	(1) OLS	(2) OLS	(3) Neg Bin	(4) Neg Bin
main				
log total recruits p.c.	0.121***	0.106***	0.059***	0.045**
	[0.038]	[0.038]	[0.022]	[0.021]
R^2	0.267	0.287		
Mean. dep. var.	1.490	1.490	1.490	1.490
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	No
Marginal effect at mean recruitment			0.086***	0.066**
			(0.031)	(0.031)
Observations	2603	2603	2603	2603

Notes: Robustness to alternative estimation methods of Equation (1). Dep. var.: number of labor saving machines. Cols 1–2: OLS (baseline). Cols 3–4: negative binomial regression.Marginal effect calculated at the mean value of total recruitment. Units of observation are 2603 equally sized hexagonal cells. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.11: Robust spatial inference: Moran's I (p-value)

Dep. var.:	Labor saving machines							
Indep. var.:	Total recruits		Navy recruits		Dist. to deep sea		Navy recruits	
Cutoff: 50 km	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cutoff: 100 km	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cutoff: 200 km	0.000	0.058	0.000	0.102	0.004	0.323	0.000	0.033
Cutoff: 400 km	0.117	0.016	0.136	0.010	0.315	0.002	0.000	0.002
Cutoff: 600 km	0.161	0.284	0.130	0.261	0.485	0.430	0.285	0.399
Specification:	OLS	OLS	OLS	OLS	RF	RF	IV	IV
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2603	2603	2603	2603	886	886	886	886

Notes: The table reports p-value of Moran's I statistics at different bandwidths. Null hypothesis is no spatial correlation in the residuals of a regression of labor saving machines on military recruitment at the specified bandwidth. Dependent variable is labor saving machines: cols 1-4: OLS; cols 5-6: reduced form; cols 7-8 IV: naval recruitment is instrumented with distance to deep sea. Cols 1-2: main explanatory variable is log total recruits per capita. Cols 3-4 and 7-8: main explanatory variable is log navy recruits per capita. Cols 6-7: main explanatory variable is distance to the deep sea. All columns include the full set of controls. Cols 2, 4, 6 and 8 also include five region fixed effects. Units of observation are equally sized hexagonal cells: there are 2603 covering the entire country (cols 1-4) and 886 within 15 km from the coast (cols 5-8).

Table A.12: Robust spatial inference: standard errors corrected with the formula of Conley (1999)

Dep. var.:	Labor saving machines							
Indep. var.:	Total recruits		Navy recruits		Distance to deep sea		Navy recruits	
Coefficient	0.121	0.106	0.080	0.084	-1.102	-1.397	0.977	1.585
Robust s.e.	(0.038)***	(0.038)***	(0.039)**	(0.041)**	(0.309)***	(0.347)***	(0.323)***	(0.535)***
Conley s.e.: 50 km	(0.043)***	(0.043)**	(0.038)**	(0.041)**	(0.556)**	(0.603)**	(0.535)*	(0.788)**
Conley s.e.: 100 km	(0.037)***	(0.034)***	(0.036)**	(0.037)**	(0.571)*	(0.601)**	(0.569)*	(0.812)*
Conley s.e.: 200 km	(0.035)***	(0.029)***	(0.040)**	(0.038)**	(0.517)**	(0.509)***	(0.625)	(0.886)*
Conley s.e.: 400 km	(0.023)***	(0.018)***	(0.028)***	(0.027)***	(0.340)***	(0.343)***	(0.606)	(0.828)*
Conley s.e.: 600 km	(0.019)***	(0.015)***	(0.022)***	(0.022)***	(0.303)***	(0.278)***	(0.524)*	(0.678)**
Cluster: county	(0.042)***	(0.042)**	(0.036)**	(0.039)**	(0.539)**	(0.572)**	(0.534)*	(0.692)**
Specification:	OLS	OLS	OLS	OLS	RF	RF	IV	IV
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Standard errors corrected for spatial correlation with the formula of Conley (1999). Dependent variable is labor saving machines: cols 1-4: OLS; cols 5-6: reduced form; cols 7-8 IV: naval recruitment is instrumented with distance to deep sea. Cols 1-2: main explanatory variable is log total recruits per capita. Cols 3-4 and 7-8: main explanatory variable is log navy recruits per capita. Cols 6-7: main explanatory variable is distance to the deep sea. All columns include the full set of controls. Cols 2, 4, 6 and 8 also include five region fixed effects. Point estimates from Table 1 (cols 1-4), and Table 2-Panels B and C (cols 5-8). Standard errors underneath estimates. Row 2: heteroschedastic-robust standard errors. Rows 3–6: standard error corrected with the formula of Conley (1999). Cutoff is 50 (row 3), 100 (row 4), 200 (row 5), 400 (row 6) and 600 km (row 7). Row 8: standard error clustered at the level of 51 counties. Units of observation are equally sized hexagonal cells: there are 2603 covering the entire country (cols 1-4) and 886 within 15 km from the coast (cols 5-8). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.13: Nearest Neighbor Matching Estimates

	Labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
SATT	0.239*	0.285**	0.251**	0.278**	0.282**	0.276**
	[0.135]	[0.119]	[0.116]	[0.133]	[0.119]	[0.117]
Number of matches	1	3	5	1	3	5
Matched within region (5)?	No	No	No	Yes	Yes	Yes
Observations	2603	2603	2603	2603	2603	2603

Notes: Nearest neighbor matching. Dependent variable is number of labor saving machines. We report the average treatment on the treated: treatment is defined as being in a cell with above median recruitment. Cols 1 and 4 find for each high recruitment cell a similar observation with low recruitment. Cols 2 and 5 find three similar observations. Cols 3 and 6 find five similar observations. Cols 1-3 match on coordinates, population, agricultural share, wheat suitability and number of farm ads. Cols 4-6 use the same characteristics but require matched cells to be in the same region. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.14: Robustness to including urban areas.

	Machines				Navy recruits		Machines			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) RF	(8) RF	(9) 2SLS	(10) 2SLS
log total recruits p.c.	0.110***	0.099***								
	[0.036]	[0.037]								
log Royal Navy recruits p.c.			0.067*	0.072*					0.967***	1.594***
			[0.037]	[0.039]					[0.300]	[0.503]
Distance to deep sea					-1.165***	-0.914***	-1.127***	-1.457***		
					[0.198]	[0.212]	[0.298]	[0.338]		
Distance to the coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.264	0.282	0.262	0.281	0.326	0.353	0.273	0.289	0.037	-0.299
Mean dep. var.	1.492	1.492	1.492	1.492	-0.130	-0.130	1.443	1.443	1.443	1.443
Observations	2775	2775	2775	2775	960	960	960	960	960	960

Notes: Robustness: sample includes cells with log 1801 density above -9. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: reduced form estimates. Cols 9–10: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–10: number of labor saving machines; cols 5–6: log Royal Navy recruits per capita; we follow Chen and Roth (2023) and assign -2 to places with no recruits. Units of observation are: cols 1–4: 2775 equally sized hexagonal cells; cols 5–10: 960 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.15: Robustness **to** excluding cells with no farm ads.

	Machines				Navy recruits		Machines			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) RF	(8) RF	(9) 2SLS	(10) 2SLS
log total recruits p.c.	0.133***	0.118***								
	[0.042]	[0.042]								
log Royal Navy recruits p.c.			0.086**	0.093**					0.998***	1.594***
			[0.042]	[0.044]					[0.354]	[0.553]
Distance to deep sea					-1.138***	-0.928***	-1.135***	-1.480***		
					[0.223]	[0.241]	[0.345]	[0.384]		
Distance to the coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.286	0.303	0.284	0.302	0.248	0.276	0.300	0.312	0.096	-0.197
Mean dep. var.	1.684	1.684	1.684	1.684	-0.162	-0.162	1.629	1.629	1.629	1.629
Observations	2299	2299	2299	2299	784	784	784	784	784	784

Notes: Robustness: sample excludes cells where no farm ads was found on British newspapers. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: reduced form estimates. Cols 9–10: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–10: number of labor saving machines; cols 5–6: log Royal Navy recruits per capita; we follow Chen and Roth (2023) and assign -2 to places with no recruits. Units of observation are: cols 1–4: 2299 equally sized hexagonal cells; cols 5–10: 784 equally sized hexagonal cells lying within 15 Km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.16: Robustness to excluding areas close to victualling centers.

	Machines				Navy recruits		Machines			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) RF	(8) RF	(9) 2SLS	(10) 2SLS
log total recruits p.c.	0.124***	0.109***								
	[0.038]	[0.038]								
log Royal Navy recruits p.c.			0.087**	0.090**					1.016***	1.650***
			[0.040]	[0.042]					[0.331]	[0.558]
Distance to deep sea					-1.123***	-0.870***	-1.142***	-1.435***		
					[0.206]	[0.222]	[0.314]	[0.352]		
Distance to the coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.269	0.289	0.267	0.288	0.260	0.292	0.290	0.306	0.050	-0.284
Mean dep. var.	1.494	1.494	1.494	1.494	-0.295	-0.295	1.456	1.456	1.456	1.456
Observations	2572	2572	2572	2572	857	857	857	857	857	857

Notes: Robustness: sample excludes cells within 10 km from a victually center used by the military to supply troops. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: reduced form estimates. Cols 9–10: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–10: number of labor saving machines; cols 5–6: log Royal Navy recruits per capita; we follow Chen and Roth (2023) and assign -2 to places with no recruits. Units of observation are: cols 1–4: 2544 equally sized hexagonal cells; cols 5–10: 830 equally sized hexagonal cells lying within 15 Km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.17: Robustness to excluding Wales.

	Machines				Navy recruits		Machines			
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) RF	(8) RF	(9) 2SLS	(10) 2SLS
log total recruits p.c.	0.123***	0.111***								
	[0.043]	[0.043]								
log Royal Navy recruits p.c.			0.081*	0.092**					1.307***	2.398***
			[0.043]	[0.045]					[0.449]	[0.926]
Distance to deep sea					-0.963***	-0.685***	-1.259***	-1.642***		
					[0.215]	[0.228]	[0.341]	[0.386]		
Distance to the coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.266	0.285	0.264	0.284	0.269	0.290	0.284	0.298	-0.061	-0.856
Mean dep. var.	1.591	1.591	1.591	1.591	-0.189	-0.189	1.591	1.591	1.591	1.591
Observations	2346	2346	2346	2346	789	789	789	789	789	789

Notes: Robustness: sample excludes all cells in Wales. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: reduced form estimates. Cols 9–10: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–10: number of labor saving machines; cols 5–6: log Royal Navy recruits per capita; we follow Chen and Roth (2023) and assign -2 to places with no recruits. Units of observation are: cols 1–4: 2346 equally sized hexagonal cells; cols 5–10: 789 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.18: Alternative measure of recruitment: recruits per men.

	Lab sav machines				Navy recruits p.m.		Lab sav machines	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) IV	(8) IV
log total recruits per men	0.093***	0.081***						
	[0.031]	[0.031]						
log Royal Navy recruits per men			0.061**	0.064**			0.811***	1.307***
			[0.031]	[0.033]			[0.268]	[0.440]
Distance to deep sea					-1.358***	-1.069***		
					[0.246]	[0.269]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.267	0.287	0.265	0.286	0.272	0.304	0.061	-0.232
Mean dep var	1.490	1.490	1.490	1.490	0.173	0.173	1.442	1.442
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Robustness: recruitment is measured in log recruits per 1801 men. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–8: number of labor saving machines; cols 5–6: log Royal Navy recruits per men; we follow Chen and Roth (2023) and assign -2 to places with no recruits. Units of observation are: cols 1–4: 2603 equally sized hexagonal cells; cols 5–8: 886 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.19: Alternative measure of recruitment: assigning -1 to cells with no recruitment.

	Lab sav machines				Navy recruits p.c.		Lab sav machines	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) IV	(8) IV
log total recruits p.c.	0.181***	0.165***						
	[0.053]	[0.053]						
log Royal Navy recruits p.c.			0.126**	0.133**			1.359***	2.230***
			[0.057]	[0.060]			[0.458]	[0.777]
Distance to deep sea					-0.811***	-0.626***		
					[0.157]	[0.166]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.269	0.289	0.266	0.287	0.236	0.269	0.015	-0.372
Mean dep var	1.490	1.490	1.490	1.490	0.094	0.094	1.442	1.442
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Robustness: recruitment is measured in log recruits per 1801 people, cells with no recruitment are assigned -1. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–8: number of labor saving machines; cols 5–6: log Royal Navy recruits per men. We follow Chen and Roth (2023) in modelling explicitly the extensive margin: in this table we assign -1 to places with no recruits. In the first stage, where recruitment is the dependent variable this implies that the extensive margine is valued at 100 log points. Units of observation are: cols 1–4: 2603 equally sized hexagonal cells; cols 5–8: 886 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.20: Alternative measure of recruitment: assigning -3 to cells with no recruitment.

	Lab sav machines				Navy recruits p.c.		Lab sav machines	
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FS	(6) FS	(7) IV	(8) IV
log total recruits p.c.	0.083***	0.070**						
	[0.029]	[0.029]						
log Royal Navy recruits p.c.			0.054*	0.056*			0.762***	1.229***
			[0.029]	[0.030]			[0.252]	[0.415]
Distance to deep sea					-1.446***	-1.137***		
					[0.263]	[0.287]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.266	0.287	0.265	0.286	0.270	0.301	0.060	-0.236
Mean dep var	1.490	1.490	1.490	1.490	-0.648	-0.648	1.442	1.442
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Robustness: recruitment is measured in log recruits per 1801 people, cells with no recruitment are assigned -3. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: first stage estimates. Cols 7–8: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables are: cols 1–4 and 7–8: number of labor saving machines; cols 5–6: log Royal Navy recruits per men. We follow Chen and Roth (2023) in modelling explicitly the extensive margin: in this table we assign -3 to places with no recruits. In the first stage, where recruitment is the dependent variable this implies that the extensive margine is valued at 300 log points. Units of observation are: cols 1–4: 2603 equally sized hexagonal cells; cols 5–8: 886 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.21: Alternative measure of adoption: threshing machines.

	Threshers							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) RF	(6) RF	(7) 2SLS	(8) 2SLS
log total recruits p.c.	0.049***	0.041***						
	[0.013]	[0.014]						
log Royal Navy recruits p.c.			0.056***	0.048***			0.473***	0.542**
			[0.015]	[0.016]			[0.149]	[0.219]
Distance to deep sea					-0.534***	-0.478***		
					[0.149]	[0.166]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.192	0.207	0.193	0.208	0.253	0.257	-0.011	-0.079
Mean dep var	0.556	0.556	0.556	0.556	0.666	0.666	0.666	0.666
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Robustness: labor saving machines only include threshers. Cols 1–4: OLS estimates of Equation (1). Cols 5–6: reduced form estimates. Cols 7–8: IV estimates of Equation (1); instrument of naval recruitment is distance to the deep sea. Dependent variables is number of threshers. Units of observation are: cols 1–4: 2603 equally sized hexagonal cells; cols 5–8: 886 equally sized hexagonal cells lying within 15 km from the coast. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.