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

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Abstract

We collect new data and present new evidence on the effects of labor scarcity on the adoption of labor-saving technology in industrializing England. Where the British armed forces recruited heavily, more machines that economized on labor were adopted. For purposes of identification, we focus on naval recruitment. Using warships' ease of access to coastal locations as an instrument, we show that exogenous shocks to labor scarcity led to technology adoption. The same shocks are only weakly associated with the adoption of non-labor saving technologies. Importantly, there is also a synergy between skill abundance and labor scarcity boosting technology adoption. Where labor shortages led to labor-saving machine adoption, technology afterwards improved more rapidly.

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

JEL Classification Numbers: N13, N43, O14, O31, O47.

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Before the Industrial Revolution, output per capita and living standards stagnated for millennia – Malthusian forces nullified the gains from technological progress (Galor, 2005). As industry modernized in parts of Britain around the middle of the 18th century, growth and technological change accelerated – slowly at first and then rapidly, eventually outpacing population growth (Crafts and Mills, 2020). While many factors have been invoked to explain the transition to self-sustaining growth (Jones, 2001), understanding the accelerating pace of technological change is central to any wider explanation. 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) or Acemoglu (2007). In contrast, Mokyr (2016) emphasizes cultural factors such as the Enlightenment and human capital – the need to combine high-end ability 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).

Examining the causal role of factor scarcity in the transition to self-sustaining growth is challenging. Credible analysis requires cross-sectional variation in labor supply, across a set of local labor markets. Such variation should also be exogenously assigned, and not just reflect local economic conditions. Moreover, detailed data on skill availability and the cost of skilled labor are scarce, as is information on the adoption of new technologies. Whether labor shortages facilitated the transition to self-sustaining growth remains an open question (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. We focus on technology adoption, not invention, since productivity growth ultimately depends on usage. To measure tech-

[1] Which 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).

nological change, we collect new, granular data on the diffusion of technologies (both labor-saving and not) in England. The French Revolutionary and Napoleonic Wars (1793-1815) saw a rapid expansion of Brtain's armed forces, leading to significant labor market imbalances. These were large enough to shift local sex ratios decisively in favor of women (in-migrants did not compensate for the recruited men).Labor saving machines, including the iconic threshing 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 often carried out by press-gangs which compelled individuals to serve involuntarily (Rodger, 2006).[4] Since each captain was responsible for manning his own ship such recruitment was also decentralized. Within 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 local skill supply combined to further increase technology adoption and the rate of

[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.

productivity improvement, along the lines of recent work by Kelly et al. (2022). Our results demonstrate that labor shortages and the availability of mechanical skills in combination facilitated technological progress. We use data on apprenticeship contracts to measure local skill supply. In locations where young men trained as blacksmiths, watchmakers, and millwrights, labor shortages translated into much greater increases in technology adoption than in places without such specialists. The same pattern is visible for technology improvements — in locations with many local craftsmen, military recruitment led to more participation in 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 newly-collected data comprising three main datasets. First, we compile the first comprehensive individual-level database of military recruitment in England during the Napoleonic Wars, using data from the army and the navy. Both the army and navy expanded rapidly after 1793. At their peak they had an estimated 350,000 men under arms. The British Army recruited across the country, but more heavily in some areas than others – especially those 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. In order to capture the geographical distribution of this recruitment, we hand-collected and transcribed a large sample of muster-rolls – personnel records of individual ships, randomly sampled. From these records, we digitize information on the geographical origin of recruits which allows us to map the geography of labor supply shocks driven by 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 1800-1830 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 labor shortages during the Napoleonic Wars facilitated innovation and technological improvements in later decades: 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, as predicted by our instrument, 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 examine the effect of alternative indicators of recruitment and technology adoption, and find results to be consistent. Finally, we show that possible limitations of our data source for adoption, newspapers, do not affect our conclusions.

We contribute to two main strands of literature. 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 19th 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 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 (Trew, 2020), 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 (Mokyr et al., 2022; 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 and do not need assumptions on how high wages translated into higher real labor costs. 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

[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.

[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.

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.

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 and background for this mechanism, describing Britain's economic transformation after 1750, before summarizing the state of agriculture and the general 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 (Broadberry et al., 2015). Most of this increase was driven by population growth, with real per capita income growth in the 0.3-0.9% range. Total factor productivity growth was similarly sluggish, averaging 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 (Crafts and Mills, 2020; 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, with the share of people employed higher than the share of output (Crafts, 1985). In contrast, in Britain these shares were equal at 31% as early as 1801 (Broadberry et al., 2015). 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. Britain succeeded in "releasing" surplus labor from agriculture long before other countries (Crafts, 1985).

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 at a time when continental agriculture was largely based on self-sufficient peasant agriculture (Wrigley, 1985). New methods such as crop rotations, fertilization, and drainage boosted productivity.

Hired labor was key for operating large-scale, efficient farms. A substantial share of work was performed by agricultural servants, employed on year-round contracts (Kussmaul, 1990). Farmers also hired agricultural day laborers on a seasonal basis. During the early modern period, these laborers often lost access to the village commons – 71% of agricultural land was enclosed by 1700 – making them increasingly reliant on wage income (Allen, 1992). Britain operated a generous system of income support known as the Poor Law (Boyer, 1990). Relief could only be received by those having a "settlement" in a parish (obtained by birth, marriage, or apprenticeship). Therefore, to leave meant to lose access to income support. In this way, the Poor Laws discouraged labor mobility.

Several new agricultural technologies emerged during the Industrial Revolution. Some of these technologies were labor-saving, replacing activities that previously required great labor input. Threshing carried out in the traditional way was particularly labor-intensive. It accounted for approximately half of all labor performed on English farms from November to March. The first threshing machine was invented in Scotland by the engineer Andrew Meikle, in the late 18th century. Originally powered by horses, they were quickly combined with water power and eventually with steam engines, yielding important increases in per capita output (Caprettini and Voth, 2020). Initially, high costs and low reliability limited adoption to northern England, where agricultural wages were higher (Macdonald, 1975; Caird, 1852). The 1799 edition of the General View of Agriculture of Yorkshire notes:

> *These machines [. . .] have lately been successfully introduced into the northern counties of England, though, strange to tell, they are scarcely known in the southern and best cultivated parts!*

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 conducted a survey of working and employment conditions in Britain in 1832. The return from Burnham, a village in Buckinghamshire, illustrates the impact of threshing machines:

> *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."

This exchange also illustrates why wages may be a poor indicator of labor market conditions – according to the testimony, labor demand for threshing fell sharply, but wages did not adjust.

Most calculations suggest that threshers increased labor productivity by a factor of five (Caprettini and Voth, 2020). Additional labor-savings were made with the introduction of horse hoes that removed weeds and horse rakes that collected hay into bales. The labor savings here were also considerable: 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 in 1830 (the last year in our newspaper data) reaper technology was still rudimentary (Fussell, 1952). In contrast, turnip cutters, chaffing machines and cake crushers did not save labor. They 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).

1.3 Britain during the Napoleonic Wars

The wars against revolutionary France and Napoleon last for almost a quarter of a century, from 1793-1815. While coalitions came and went, Britain was at war with France throughout, except for the brief Peace of Amiens (1802-03). At its peak, Napoleonic France had conquered most of continental Europe. In turn, the United

Kingdom successfully seized most of the overseas possessions of France and her allies. The UK relied on a large fleet to support its allies, to conduct amphibious landings, to cut France and her allies off from her colonies, and to 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), repaying its debts gradually in peacetime. 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 navy's size had declined to only 14,000 men, while the army was down to 110,000 (Clowes, 1899; Fortescue, 1899). Thus 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): a massive labor market shock.[8]

Not only did the military expand greatly, 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 have been estimated at over 300,000 cumulatively over the period 1804-1815 – 90,000 for the Royal Navy and 220,000 for the British Army (Dumas and Vedel-Petersen, 1923). Because such losses had to be compensated by continual recruitment, maintaining armed forces equivalent to 10-14% of the adult male population required cumulatively an even higher proportion of all men.

The British Army mainly recruited from the lower classes. Pay was low and conditions were harsh; except for day laborers, petty criminals, and vagrants, few

[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 (the age is available in the 1851 Census, when 60% of the population was between 11 and 50 years old).

joined the colors. The Duke of Wellington, who led the British Army to victory in 1815, famously observed: "We have in the service the scum of the earth as common soldiers." Some 43 percent of army recruits were day laborers, and an additional 7 percent, farmers (Floud et al., 1990). Thus, massive recruitment of the British Army directly contributed to rural labor shortages.

Naval recruitment created additional pressures on the civilian labor market. The navy needed able seamen and sought to recruit merchant sailors. Impressment (lawful but involuntary service) was common. Navy recruitment was also decentralized: each captain had to man his own ship. Once in the navy, recruits were routinely assigned to other Royal Navy vessels. Pressing sailors arguably created indirect pressure on the local labor employed in non-seafaring activities because some men working elsewhere joined the merchant marine. As both the Royal Navy and the merchant marine grew during the wars (Dancy, 2012, reproduced in Figure A.1), naval recruitment contributed to higher labor demand in the areas exposed to impressment. Our IV strategy exploits determinants of naval recruitment to estimate the causal effect of recruitment on adoption.

Recruitment intensity varied over space and migration did not offset this effect. Some recruits came from abroad: many sailors were Irish, others were American or European (Dancy, 2018; in our data, 10 percent of recruits are Irish). Fewer soldiers were of foreign origin, but some army units were raised abroad. However, the vast majority of military men came from Britain. As the quote from the General Views of Agriculture suggests, the consequences of these war-induced labor shortages on adoption were obvious already 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 over time and space, 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 periodically (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 and we are able to geolocate around 64 percent of this sample in either England or Wales (around 15,000 recruits). Floud was interested in estimating anthropometric measures of British soldiers, and digitized a random sample of new recruits in every decade: his sampling procedure provides reasonable geographical coverage (Figure 1 – Panel A).

Royal Navy. We introduce a new database of naval recruitment digitized from the original ships' muster rolls. Similar to those collected by the army, these accounting records were compiled aboard each Royal Navy ship every two months by the purser. At the time of the Napoleonic Wars, these records were standardized across the Navy and included space for the reporting of, among other attributes, each man's name and place of birth, as well as their rank and an indication of whether they were pressed into service. Not all individual records include a birth place, some include one that is inadequately precise (e.g. the county), some are illegible, while others record a birthplace that is overseas.

We combine three different samples of ship records. In total, they 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)

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

(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 of ships is balanced in terms of size (as proxied by the number of guns) and port of commission (Chatham, Portsmouth and Plymouth). Out of 95 thousand records, we can assign over thirty thousand to a parish in England and Wales using the birthplace recorded in the musters. Random selection of ships, combined with sailor rotation, ensures that our sample is representative of the population of Royal Navy sailors.

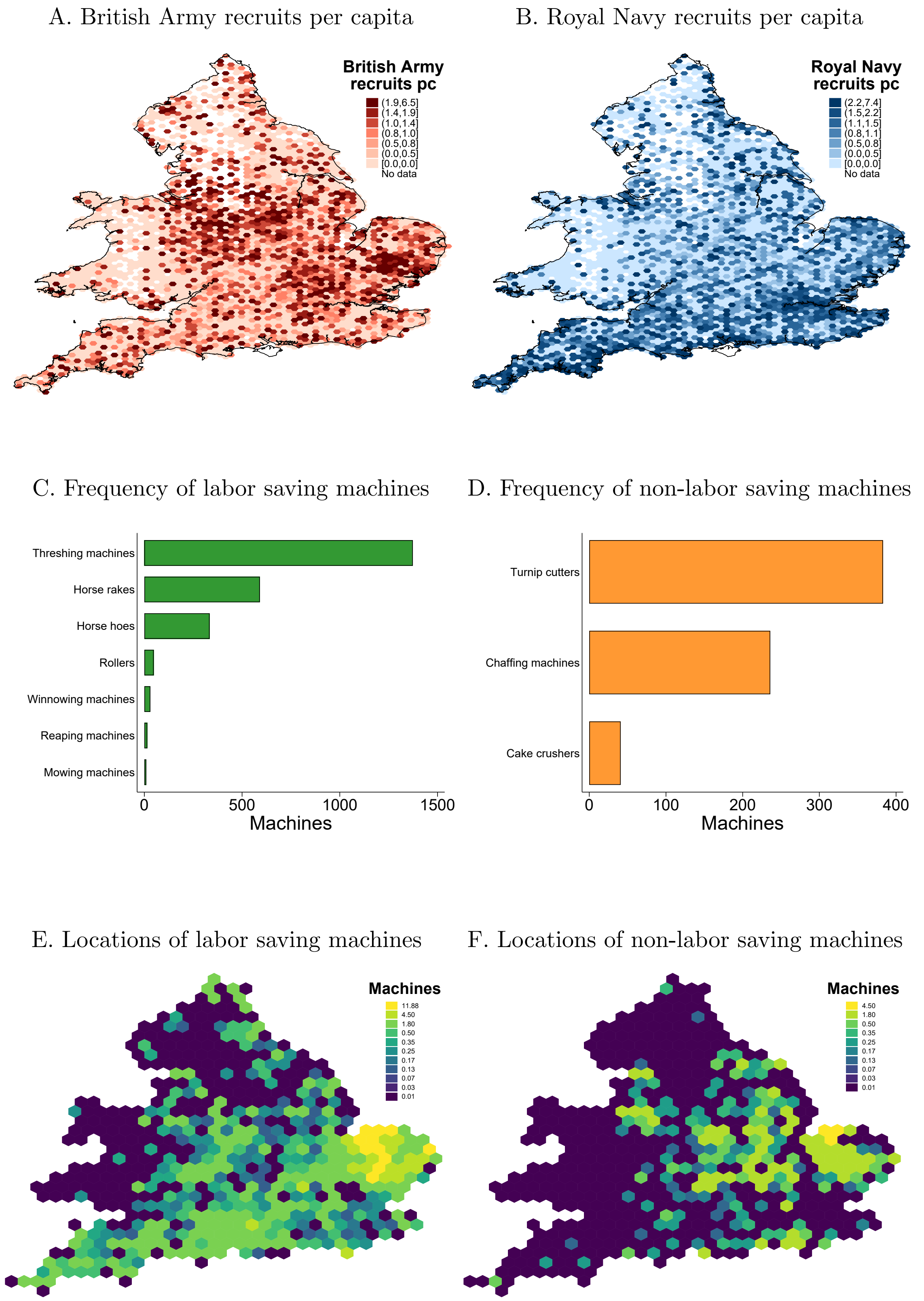
Geographical distribution and involuntary recruitment. Panels A and B of Figure 1 summarize the geography of military recruitment in England and Wales, with darker cells experiencing higher recruitment rates. While many men came from coastal areas, particularly in the Navy, recruits in both forces were drawn from all across England and Wales. Major population centers, as well as ports, were important sources of manpower. Based on the sample of recruits that we collected (which is the only dataset for which we have ratings and volunteer information), 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 would be of minor importance.

2.2 Machines

We derive measures of technology adoption from historical advertisements extracted from a corpus of 19th century local newspapers (British Library and Findmypast, 2022). When farms were sold, their inventory of machines would typically be sold

[10]Of the total sample, only 13.6% are recorded in the muster roll as volunteers; an upper bound on the involuntary share is thus 86.4%. While there was an incentive to be recorded as voluntary in muster books, since this would have been required for any bonus to be delivered for volunteering, there would have been many aboard ship voluntarily that would not be recorded as such, particularly those at higher ratings. If all officers are voluntary, we are left with the seamen (that is, those rated "able", "ordinary", "landsman" and "boy"). This group represents 62.4% of all men in our sample. Only 17.8% of this group are recorded in the muster roll as having volunteered, giving us our lower bound on impressment.

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



Notes: Panel A: British Army recruits in 1790s-1810s divided by 1801 population (i.h.s.). Panel B: Royal Navy recruits in 1792-1815 divided by 1801 population (i.h.s.). 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*.

with them. These machines would be listed in advertisements announcing the sale.[11] As described above, 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 3,003 machines – 2,403 labor-saving ones, and 660 non-labor saving ones (Figure 1-Panels C–D).

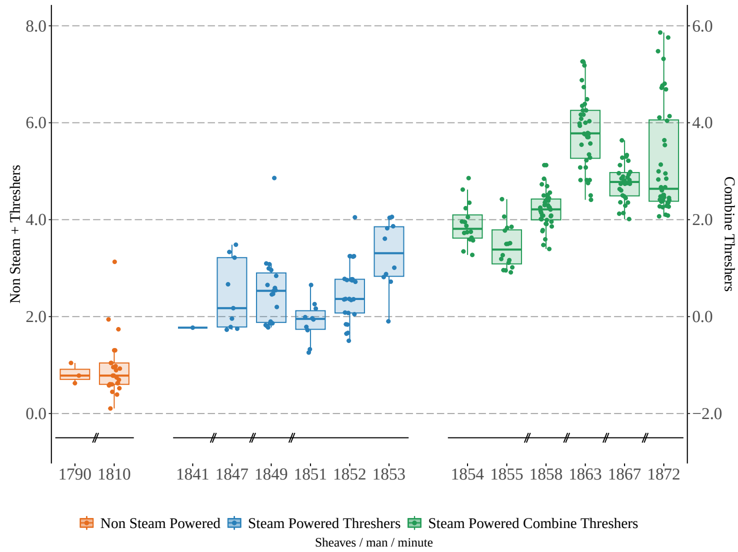
As Figure 1-Panels E–F show, we find machines across the entire country, from North to South and East to West. The majority of labor-saving machines in our data are threshers (Panel C), with non-labor saving machines more evenly balanced across types (Panel D). Figure 1-Panels E and F depict the geography of machines in use. While the rich agricultural area around Norfolk and in Cheshire saw massive adoption of both types of machinery, labor-saving machines are also found to a much greater extent across all of England and Wales. In the North, in Wales and in Cornwall, for example, non-labor saving machines made few inroads. London and its surroundings saw limited adoption of either type of machine, possibly because agriculture here catered to the city with garden crops (no cereal machines needed), but also because foodstuff would have been traded into the city from its rural surrounds.

2.3 Royal Agricultural Society Competitions

We collect detailed information on productivity of more than 300 threshers from the records of Royal Agricultural Society of England (RASE) competitions. The Society received a Royal Charter in 1840 with the mission to promote modern agricultural practices across England. From 1841, it organized periodic competitions to recognize the best design of various agricultural machines, as judged by a committee of experts. Incentives were high: winners received sizeable monetary prizes as well as publicity (Brunt et al., 2012). We collect detailed entries for the performance of 306 steam-

[11]This dataset builds on Caprettini and Voth (2020) and uses the same source, but extends the range of agricultural machinery considerably.

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 is equivalent to roughly 1.5kg: we convert all observations into the most common measure used at the time. *Sources*: 1790s and 1810s: *General Views of Agriculture*; 1841-1872: Royal Agricultural Society of England Meeting competitions.

powered threshing machines presented at fifteen meetings between 1841 and 1872. We harmonize data and derive comparable measures of thresher productivity in terms of sheaves of wheat threshed in one minute by one man operating the machine. To our knowledge, this is the first database with information on the productivity of early threshers. Figure 2 shows the data from these competitions along with earlier productivity data from the *General Views of Agriculture*. Machines became more complex overtime, first accommodating steam-power and later integrating new tasks (combine threshers). Despite substantial variation at any one moment in time, there is a clear upward trend in average productivity.[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 first population censuses of

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

1801 and 1811 (Southall et al., 2020).[13] We calculate the distance from the centroid of every cell to the coast as well as to the closest sea point 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] Data on 18$^{\text{th}}$ century English apprentices are from the Board of Stamp's Apprenticeship Books (see also Feldman and van der Beek, 2016). These volumes record the payment of statutory duties for the employment of indentured apprentices. We use the source to locate metal workers and watchmakers indentured between 1710 and 1791. Next, we digitize the parish of origin of every inventor who filed a British patent between 1700 and 1792 from Woodcroft (1854) and create an indicator for cells where at least one of these inventors lived. 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 before 1792 and create an indicator variable for the presence of an engine. Country banks are from Dawes and Ward-Perkins (2000). Wheat suitability is from FAO-GAEZ (Fischer et al., 2021) and refers to the potential yield of wheat under medium levels of inputs. We calculate two more distances: to the closest town with a newspaper and to one of the towns with a post office in 1792. We derive the list of newspaper towns from metadata of the corpus of historical journals (British Library and Findmypast, 2022). The list of post towns at 1791 is from Robertson (1961). Appendix A.2 provides details on variable construction.

3 Main Empirical Results

In this section, we first present a bird's-eye view of how military recruitment led to labor scarcity. We show that local recruitment caused local gender imbalances, suggesting that vacancies were not simply filled by men from other areas. In turn,

[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.

labor scarcity is strongly positively correlated with the adoption of labor-saving technologies. Crucially, we find that labor shortages do not predict the adoption of non-labor saving technology. We then present an IV strategy that allows us to identify the casual effect of labor shortages. We conclude with two additional results. First, skill abundance reinforced labor scarcity in promoting technology adoption. Second, adoption 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, an indication that internal migration did not compensate for the war's missing men. 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 1.4% and 1.8% more women per man in 1801 and 1811 respectively (peak recruitment is around 1811).[15]

When we analyze the pattern for our entire sample, we find that military 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 demographic and geographic characteristics (cols 2 and 5), and after adding region fixed effects (cols 3 and 6). Effects are also large – the elasticity calculated from col 3 (col 6) implies that doubling military recruitment increased gender imbalances in 1801 (1811) by 0.7 percentage points (1 percentage point).[16] Because gender ratios at birth are close to one everywhere, these results suggest that military recruitment created significant variation in labor shortages and that internal migration did not equalize the distribution of missing men, arguably because there were significant impediments to internal mobility (see Section 1.2).

Next, we examine the association between military recruitment and machine adoption. In Figure A.3, we present a map of England in which the more blue a

[15]We use throughout the inverse hyperbolic sine transformation of the main variables and calculate elasticities with Bellemare and Wichman (2020) formulae.

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

location, the higher the rate of labor-saving machine adoption; the more red, the higher the level of recruitment by the Royal Navy. Where both coincide – as our hypothesis predicts – the darker the color of the hexagon overall. Light areas show either little recruitment or limited labor-saving machine adoption. As is readily apparent, while there are numerous blue and red observations, there are also a large number of light, grey, and dark hexagons – areas where either high recruitment coincided with high rates of labor-saving machine adoption, or 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. Nonetheless, areas with high/high and low/low values are visible across the entire length of England and Wales: they alone account for two-fifths of all cells, 23% more than that what a random assignment would predict.

Figure 3 examines these patterns systematically in the cross-section, for labor-saving and non-labor saving machines, using binscatters. 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).

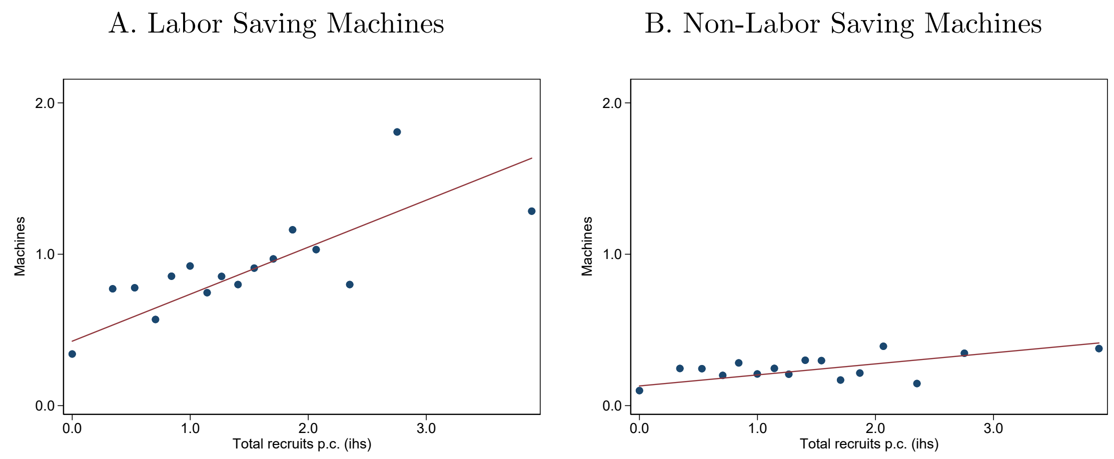
3.2 OLS Results

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. First, demographic factors such as population size and the share employed in agriculture and trade in 1801 influences the size of the agricultural sector and its demand for machines. Second, economic factors such as the availability of finance may affect farmers' ability to purchase new machines: we proxy for these factors with the presence of country banks in 1800-30. Third, the initial local level of technological development may influence a farmer's decision to introduce new machines. We proxy for the initial technological level with three indicators. The first identifies cells where between 1710 and 1791 at least one

Figure 3: Military recruitment and machine adoption



Notes: Military recruitment and machine adoption. Both panels are unconditional binscatters of total military recruits in 1790s-1810s per 1801 population (i.h.s., x-axes) on agricultural machine adoption in 1790-1830 (y-axes). We create 20 bins of equal sample size; since the first 5 bins have no variation in military recruitment we combine them into a single data point. Panel A: labor-saving agricultural machines. Panel B: non-labor saving agricultural machines.

"mechanic" (e.g. wheelwrights, watchmakers and blacksmiths) received his apprenticeship. Second, we track the spread of the most iconic invention of the Industrial Revolution by controlling for the presence of a steam engine in 1706-1791 (Kanefsky and Robey, 1980). The third indicator of technological development tracks local inventors who filed an English patent between 1700 and 1791 (Woodcroft, 1854). Fourth, geographic conditions may also affect the profitability of new machines: we control for area, suitability to wheat cultivation (Fischer et al., 2021), and two distances: to the closest town with a post office in 1791, and to the closest newspaper from which we extract machine advertisements. Both towns with a post office and a newspaper are likely to be centers of the diffusion and adoption of new ideas. Controlling for distance to newspaper towns is also important because our data may oversample areas covered by local newspapers (Beach and Hanlon, 2022). In the most conservative specification, we include five region fixed effects α_r which absorb potentially different labor market conditions across England (Caird, 1852).

We explore the basic patterns, conditional on an expanding set of control variables, in Table 1. Our units of observation are around 2,600 equally-sized cells covering England and Wales. 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 larger impact.

The effects are important. Our baseline result suggests that a one standard deviation (s.d.) increases in recruitment per capita raised labor-saving machine adoption by 0.16 of a s.d. Once we control for other variables, the size of the coefficient falls, but remains large and significant even in the most demanding specifications. The use of additional controls only leads to minor reductions in coefficient size, reducing concerns over omitted variables.

Recruitment mattered much less for the adoption of non-labor saving machines. For these technologies, unconditional OLS estimates also suggest a significant effect, but of a smaller magnitude of 0.09 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 adoption of non-labor saving machines. However, the point estimate of army recruits is one-quarter 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 on 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.

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

Panel A: Labor saving machines and recruits

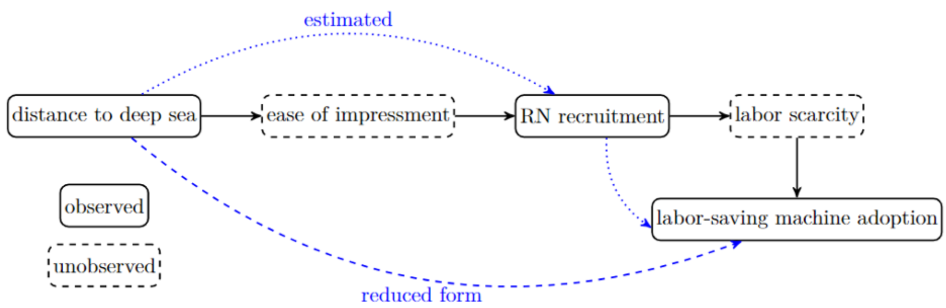
	Labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
Total recruits p.c. (i.h.s.)	0.310***	0.236***	0.210***	0.167***		
	[0.046]	[0.047]	[0.045]	[0.043]		
Royal Navy recruits p.c. (i.h.s.)					0.108**	
					[0.048]	
Army recruits p.c. (i.h.s.)						0.228***
						[0.059]
R^2	0.026	0.053	0.076	0.129	0.125	0.132
Mean. dep. var.	0.786	0.786	0.786	0.786	0.786	0.786
Demographic and geographic controls	No	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	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)
Total recruits p.c. (i.h.s.)	0.073***	0.047**	0.028	0.023		
	[0.020]	[0.021]	[0.021]	[0.021]		
Royal Navy recruits p.c. (i.h.s.)					0.007	
					[0.024]	
Army recruits p.c. (i.h.s.)						0.059**
						[0.026]
R^2	0.009	0.025	0.043	0.049	0.048	0.052
Mean. dep. var.	0.215	0.215	0.215	0.215	0.215	0.215
Demographic and geographic controls	No	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	No	No	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	Yes	Yes	Yes
p-value lab sav = non lab sav	0.000	0.000	0.000	0.000	0.024	0.001
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.

Figure 4: IV Strategy



Notes: The figure summarizes the IV-strategy. Solid arrows indicate hypothesized causal links.

3.3 IV results

The OLS results could be biased for several reasons. We observe only a fraction of total recruitment and so large measurement error in our main explanatory variable 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 motivated by the nature of naval recruitment. Royal Navy recruitment was heavily decentralized, with every captain responsible for finding the sailors needed. Captains used a combination of incentives and force to man their vessels. Impressment was a major source of manpower for the Royal Navy, accounting for at least half of all sailors (Rodger, 2006). The practice took a variety of forms – Royal Navy ships might stop merchant vessels on the high sea, or seize sailors out of docked ships in port. They would also send press gangs led by a lieutenant to raid local pubs and gathering places in order to conscript men. While press gangs were unpopular and sometimes over-eager, this form of involuntary conscription was legal and sanctioned by the state. In order to press men, a navy vessel would anchor out at sea and send in its smaller boats such as the longboat or jolly boat, which would then need to cross the open sea to reach the nearest beach.

As our instrument, we use the ease with which any coastal location could be reached by these boats. Rowing or sailing small boats over the open sea was only feasible for limited distances – if navy ships had to anchor too far out at sea, the process would be too slow and hazardous. Because most naval recruitment was carried out by ships much larger than civilian ships, we can also separate military labor demand from that of the merchant marine. Our instrument thus directly avoids one immediate concern, that the focus on maritime districts may only pick up the effects of trade. The implementation of our instrument is based on a close reading of the technical characteristics of military ships in the Age of Sail. The mainstay of British naval power, the ships of the line, had a draft of around 10m. To avoid becoming stranded, ships typically anchored at a minimum depth of fall of the tide + draught vessel + minimum clearance (FUD rule, see Figure A.4). With a 2m minimum, and a typical UK fall of the tide of 2-4m, this translates into 14-16m for ships of the line (first-rate to third-rate).

We restrict our sample to "coastal cells", composed of grid cells no farther than 15km from the coast. This yields 886 coastal cells, 34% of the full sample. We always control for the distance to the coast to account for the impact that sea proximity may have on technology adoption even within the coastal sample. 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 through its impact on naval recruitment.

To build intuition, consider the two cells covering the ancient hundreds of 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. Both are 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: no country banks opened during the Napoleonic Wars, and until 1792 we find no mechanic apprentice, no British inventor, nor a single Newcomen steam engine. In short, on the eve of the Napoleonic Wars, little set these two hundreds apart. 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). In line with the logic of our IV-strategy, the Royal Navy recruited in Smithdon but not in Clockclose, resulting in greater gender imbalances (1.05 vs 1 women per men). Greater labor scarcity also led to faster technology adoption: we find almost three times as many labor saving machines in Smithdon, close to the deep sea (14 vs 5). Our IV strategy extends this suggestive comparison to the full sample of coastal cells.

Validation. Our IV-strategy is plausible for four reasons. First, we examine the locations of Royal Navy ports and commercial ports. In the sample of coastal cells, the distance to the 15m contour lines predicts the location of navy ports but not commercial ports. Table A.2, col 1 shows a strong, significant effect of distance to the deep sea, with every doubling of distance reducing the probability of a navy port by 9.4%. The same is not true of commercial ports: the coefficient is half the size and insignificant (col 2). As trade may influence the labor market in many ways, the absence of correlation with commercial ports is reassuring.

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 ($p \leq 0.01$). 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 greater 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 significantly different from each other: $p \leq 0.003$).

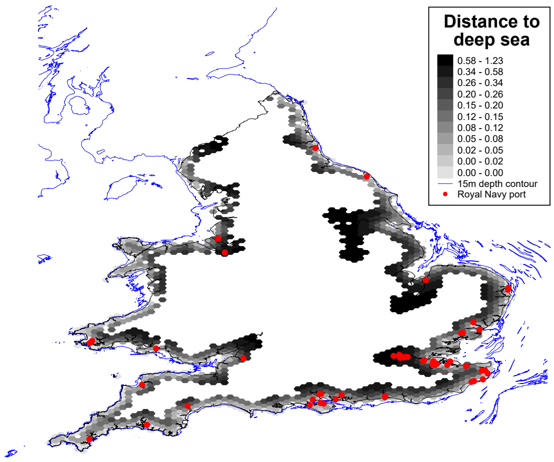
We also partition naval recruitment based on the depth of ships' hold and ask whether distance to the deep sea mattered more for ships with deeper draught. Appendix Figure A.6–Panel A provides suggestive evidence that this is the case: distance to the deep sea is a stronger predictor of those recruited into larger ships.[17] 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 twice as big as that for shallow ships, and the difference is significant in the first two columns ($p = 0.005$) though not in the last two ($p = 0.181$). 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

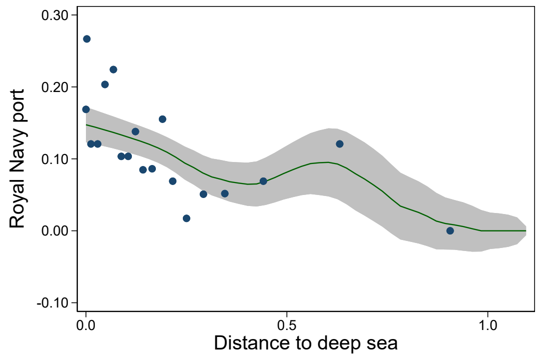
[17] We consider ships with a deep draught those with a depth of the hold of 5m or more: they are overwhelming ships of the line (90 out of 92). Sloops, frigates, cutters, gun-brig and schooners are all ships with a shallow draught. For this exercise we also consider only recruits with fewer than three 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.

Figure 5: IV strategy

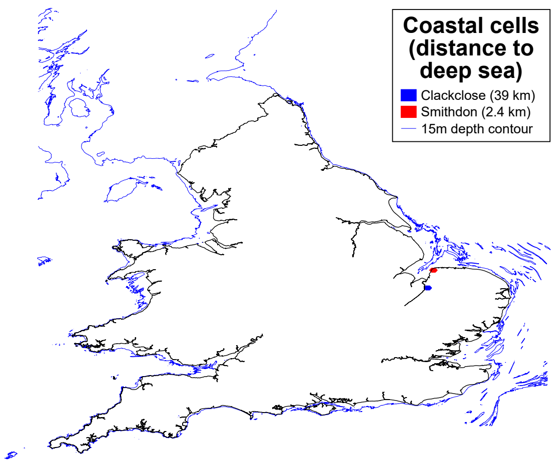
A. Deep sea and port location



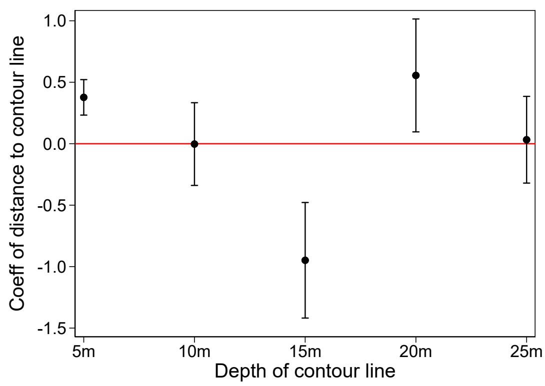
B. Navy presence and distance to deep sea



C. Example: cells with different IV exposure



D. Distance to deep sea and Navy port presence



Notes: Panel A: distance to the closest sea point 15m deep in the coastal sample; in red Royal Navy ports. The sample for Panels B and D-F consists 886 cells within 15 km from the coast. Panel B: unconditional binscatter of distance to the deep sea (x-axis) on probability of Royal Navy port (y-axis) using 20 bins of equal sample size. 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% confidence intervals.

are smaller and home fewer people. They are also more likely to be closer to the deep sea.[18] A better indicator is the fact that density (people per square meter of land in the cell, i.h.s.) 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 observables 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 present 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 0.19 s.d. The first-stage is strong, with an F-stat of 22-47, 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 $p \leq 0.01$, and confidence intervals calculated with tF method of Lee et al. (2022) do not include the zero, demonstrating the strength of our instrument (Panel D). The coefficients indicate that increasing naval recruitment by 1 s.d. led to a 0.64-0.70 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 ($p \leq 0.03$).

Never takers. One simple way to further validate our IV-exercise is to look at

[18] Indeed, because cells are equally sized, variation in the area stems from their different share of sea cover.

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

Panel A: First stage.

	Recruits p.c. (i.h.s.)			
	(1)	(2)	(3)	(4)
	Royal Navy	Royal Navy	British Army	British Army
Distance to deep sea	-0.739***	-0.585***	0.093	-0.100
	[0.119]	[0.130]	[0.110]	[0.119]
R^2	0.288	0.314	0.125	0.139
Mean. dep. var.	0.995	0.995	0.561	0.561
F-stat of excluded instrument	38.5	20.2		

Panel B: Reduced form.

	Machines			
	(1)	(2)	(3)	(4)
	Lab sav	Lab sav	Non lab sav	Non lab sav
Distance to deep sea	-1.003***	-0.747**	0.016	-0.133
	[0.288]	[0.299]	[0.110]	[0.134]
R^2	0.110	0.141	0.045	0.061
Mean. dep. var.	0.887	0.887	0.205	0.205

Panel C: Two-stage least squares. Instrument is distance to deep sea.

	Machines			
	(1)	(2)	(3)	(4)
	Lab sav	Lab sav	Non lab sav	Non lab sav
Royal Navy recruits p.c. (i.h.s.)	1.357***	1.277**	-0.022	0.227
	[0.439]	[0.579]	[0.147]	[0.234]
Mean. dep. var.	0.887	0.887	0.205	0.205
Anderson-Rubin test (p-value)	0.001	0.013		
Distance to coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes

Panel D: tF Inference

Machines (column):	tF Inference	
	5%-level	10%-level
Labor saving (1)	[0.376, 2.337]	[0.648, 2.065]
Labor saving (2)	[-0.217, 2.771]	[0.243, 2.311]
Non labor saving (3)	[-0.350, 0.306]	[-0.259, 0.215]
Non labor saving (4)	[-0.376, 0.830]	[-0.191, 0.645]

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: Never-takers

	Labor saving machines		
	(1)	(2)	(3)
	Coastal sample	Never takers	Rest
Distance to deep sea	-0.747**	-0.045	-0.793**
	[0.299]	[0.290]	[0.320]
R^2	0.141	0.472	0.137
Mean. dep. var.	0.887	0.091	0.929
Distance to coast	Yes	Yes	Yes
Demographic and geographic 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.

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 3 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.[19] There are two likely sources of bias. First, severe measurement error stems from sampling only a

[19]We find limited evidence for two alternative explanations. First, Appendix Table A.4 implements the Ishimaru (2022) method and finds that different weighting cannot explain the different size of OLS and IV. Second, 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.

portion of all active Royal Navy ships. Additionally, records are derived from handwritten 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 35% (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 ended up because of 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 Synergy of adoption with mechanical skills

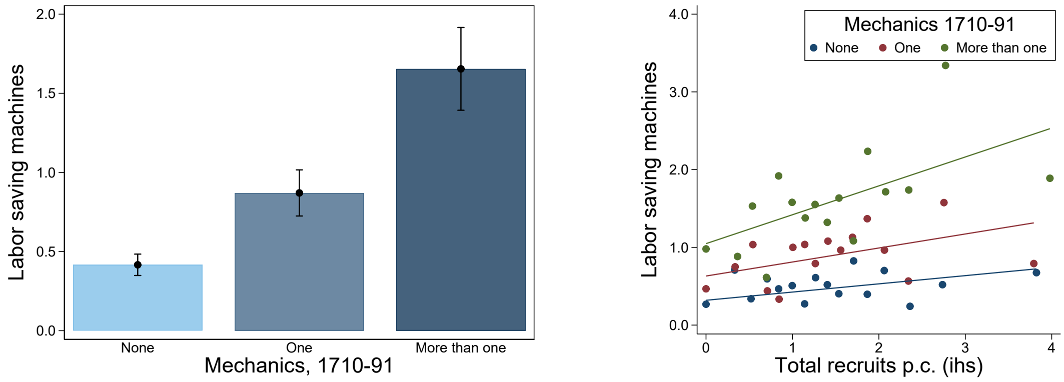
Mechanics were important for developing new machines and for maintaining them Mokyr (2009). From apprenticeship records, we collect data on the geography of mechanical skills before the outbreak of the Napoleonic Wars. These additional data allow us to identify a clear synergy – areas of Britain home to craftsmen with mechanical training show both faster adoption of labor-saving machines, and faster progress in the quality of threshing machines.

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 more than 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. The availability of local mechanics facilitated technology adoption in response to military recruitment, causing more labor-saving machine adoption where numerous mechanics were available.

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 mechanical apprentices: mean and 95% confidence intervals. Panel B: labor scarcity and machine adoption by presence of mechanics. Unconditional binscatters of total military recruits per capita (i.h.s., x-axis) on labor saving machine adoption (y-axis). Sample split in three based on number of mechanical apprentices. For each sample, we create 20 equal-size bins; the first bins have no variation in military recruitment and are combined into a single data point.

In Table 4, we show that the synergy between metal-working apprentices and labor shortages leading to labor-saving machine adoption is statistically significant – we find effects for both the intensive and extensive margin (cols 2 and 4). There is no such pattern for non-labor saving machines (cols 6 and 8). These results suggest that relative factor prices and human capital 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.

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. We first show that the number of entrants in the RASE competitions correlates positively with the number of machines in use. In Table 5, we regress the number of competitors

Table 4: Adoption: Synergies between mechanics and labor scarcity

	Labor saving machines				Non labor saving machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number	Number	Dummy	Dummy	Number	Number	Dummy	Dummy
Total recruits p.c. (i.h.s.)	0.165***	0.061	0.041***	0.026**	0.023	0.015	0.007	0.006
	[0.043]	[0.038]	[0.009]	[0.011]	[0.021]	[0.017]	[0.006]	[0.007]
Tot recruits pc × one mechanic		0.057		0.020		-0.005		0.002
		[0.075]		[0.023]		[0.041]		[0.016]
Tot recruits pc × > 1 mechanic		0.379***		0.044**		0.036		-0.000
		[0.136]		[0.022]		[0.062]		[0.016]
One mechanic	0.032	-0.005	0.019	-0.002	0.004	0.013	0.011	0.009
	[0.086]	[0.111]	[0.024]	[0.034]	[0.041]	[0.058]	[0.018]	[0.026]
> 1 mechanic	0.501***	-0.024	0.080***	0.022	0.076	0.025	0.034	0.035
	[0.131]	[0.213]	[0.028]	[0.040]	[0.053]	[0.095]	[0.021]	[0.030]
R^2	0.134	0.140	0.164	0.166	0.050	0.050	0.061	0.061
Mean. dep. var.	0.786	0.786	0.290	0.290	0.215	0.215	0.116	0.116
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	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). Cols 1–2 and 5–6: total number of machines; cols 3–4 and 7–8: at least one machine dummy. Units of observation are 2603 equally-sized cells. 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.

on the number of threshing machines adopted by 1830.[20] This suggests a strong and highly significant link between early adoptiojn on the one hand, and active involvement in "R&D" on the other.

Table 6 shows adoption and recruitment predict productivity of entrants' designs. We find that more machines in a county lead to better 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

[20] As many of the RASE participants are manufacturers in cities, we include urban cells.

Table 5: Technological progress. RASE competitors, adoption and skill abundance

	RASE entries, 1841-72			
	(1)	(2)	(3)	(4)
	Number	Number	Dummy	Dummy
Threshers within 50 Km (100s)	0.140*	0.060	0.013**	0.007
	[0.074]	[0.050]	[0.006]	[0.005]
Threshers within 50 Km (100s) × one mechanic		0.018		0.001
		[0.048]		[0.007]
Threshers within 50 Km (100s) × > 1 mechanics		0.175		0.013
		[0.208]		[0.013]
One mechanic		-0.067		-0.004
		[0.045]		[0.007]
> 1 mechanics		-0.022		0.005
		[0.218]		[0.013]
Demographic & geographic controls	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
R^2	0.035	0.037	0.067	0.070
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.

(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.

Table 6: Productivity of Thresher Designs and Its Determinants

	Productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	OLS	IV	RF
Threshers within 50 km	0.003**	0.007***				
	[0.001]	[0.002]				
Total recruits p.c. (i.h.s.)			0.631***			
			[0.232]			
Royal Navy recruits p.c. (i.h.s.)				0.377**	1.448***	
				[0.179]	[0.511]	
Distance to deep sea						-2.052***
						[0.606]
Mean dep var	2.658	2.658	2.658	2.658	2.658	2.658
Distance to the coast	No	Yes	No	No	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Technology and finance	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.

4 Robustness

We examine the robustness of our results to the use of alternative estimation techniques, as well as different measures of machine adoption and recruitment. We also show that spatial autocorrelation is only of limited concern.

4.1 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.6 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).

Second, we use discrete choice models for count variables. The first two columns of Table A.7 report our baseline OLS. The other columns have Poisson (cols 3–4) and negative binomial (cols 5–6) regressions. These confirm a strong positive relation between recruitment and machine adoption, effects are near-identical to OLS.

4.2 Matching exercises

Matching methods offer an alternative way to identify causal effects. Figure A.8 presents results from CEM, entropy balancing and 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 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, the last coefficients in Figure A.8 show nearest neighbour matching estimates, where we restrict the sample to observations that are close in geography, population, agricultural share and wheat suitability. We match each high-recruitment cell to three similar cells with low recruitment (Panel A) overall or in the same region (Panel B). Estimates are significant and close to baseline results.

4.3 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.8–Panel A displays

Moran's I p-values, which suggests spatial correlation disappears beyond 600 km. To parametrically correct standard errors, we apply the Conley (1999) formula. Table A.8–Panel B 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; 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 data.

4.4 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 - and areas with poor news coverage. Neither of these choices is crucial. Including urban cells does not affect our results (Table A.9), nor does adding cells far from newspaper towns (Table A.10).

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 promote technological progress and confound 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.10 drops 59 cells within 10 km from one of the victualling centers and Table A.12 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.9 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, military recruitment relative to parish population may not be a reliable measure of labor shortages. We re-scale recruitment by 1801 male population (see Appendix Table A.13).[21] Results remain significant in OLS and IV models. Finally, our labor-saving machinery classification may introduce errors. We re-estimate with threshers only (Table A.14) 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.

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 (O'Brien, 1989; Allen, 2009). Britain was also home to a large number of scientists 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. These recruits 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, men returned from the sea and the battlefields. However, the new machinery now in place did not go unused. Instead, it continued to replace labor. Continuous improvement in efficiency (and reliability) was one reason.

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

Detailed data from agricultural competitions shows that in places where machines had been used more due to naval recruitment 1793-1815, the scale of 'tinkering' and the pace of progress were faster. Therefore, as Allen (2009) argued, adopting new technologies responded to factor scarcity and occurred where it paid to do so. However, the artisans and experimenters highlighted by Kelly et al. (2022) also contributed to faster technological progress: places that initially adopted labor-saving technologies continued to improve them even after the initial labor shortages disappeared. 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, showing that exogenously-induced labor scarcity led to technology improvements precisely because England was a country of tinkerers.

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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.[22] 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.[23] 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.[24] 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

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

[23]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.

[24]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.

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 per 1,000 men* is Royal Navy sailors per 1,000 men. We transform each of these six variables with the inverse hyperbolic sine function.

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 search for the following exact strings: 'threshing machine,' 'reaping machine,' 'mowing machine,' 'horse rake,' 'horse hoe,' 'chaffing machine,' 'turnip cutter,' 'cake crusher'.[25] We restrict our search to articles classified as either 'advertisement' or 'classifieds.' Next, we read in full each article retrieved. 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 '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

[25] We collected ads for threshing machines in the spring of 2016 and for other machines in the fall of 2019.

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 2,403 of these machines. *Non-labor saving machines* is the sum of chaffing machines, turnip cutters and cake crushers: we observe 660 of them. We classify the machines following the historical literature (Rahm, 1844; Fussell, 1952; Walton, 1973).

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 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 $\times$ 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 inverse hyperbolic sine function.

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 inverse hyperbolic sine function.

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 inverse hyperbolic sine function.

1801 density. Density is 1801 population divided by the area of the cell (Southall et al., 2020). We transform the variable with the inverse hyperbolic sine function.

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 $\times$ 9.25 km. We first resample the raster on a finer grid of 8 $\times$ 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.

1800-30 country banks. 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. 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.

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 inverse hyperbolic sine function.

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.

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.[26] 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.

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

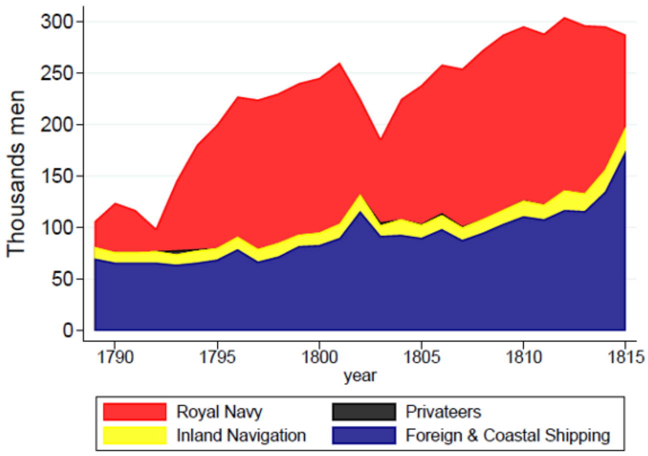
Commercial port. We compile a database of major commercial ports from Alvarez-Palau et al. (2019). The raw data contains a list of 479 historic ports and landing areas along the coasts of England and Wales. We assign a cell to a commercial port if there exists a port within 8 km from its centroid, if 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.

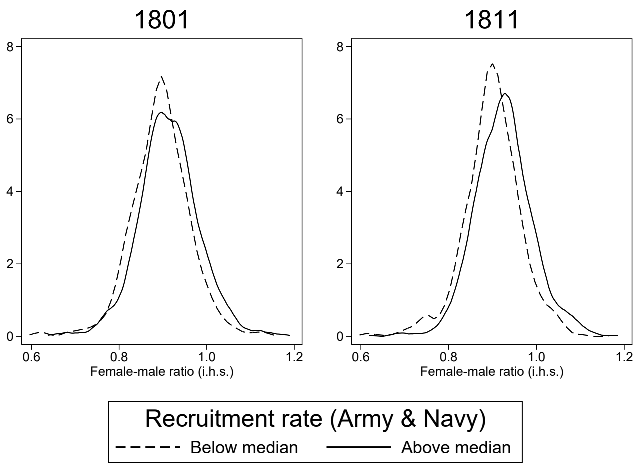
B Appendix figures

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



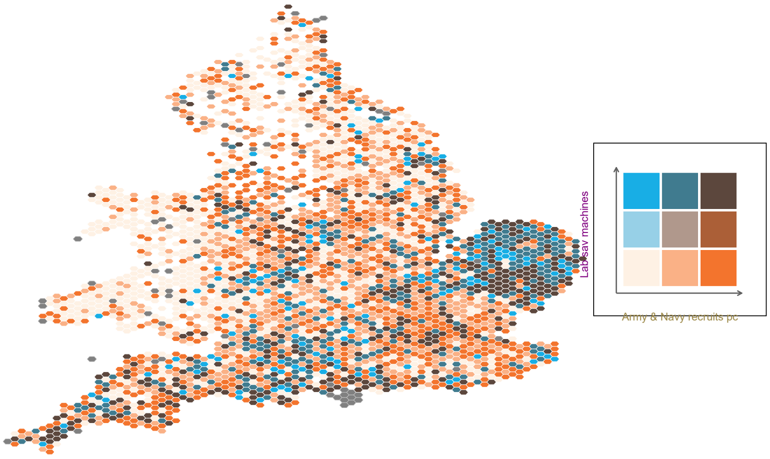
Notes: Source: Dancy (2012), Figure 2.1.

Figure A.2: Sex Ratios and Recruitment



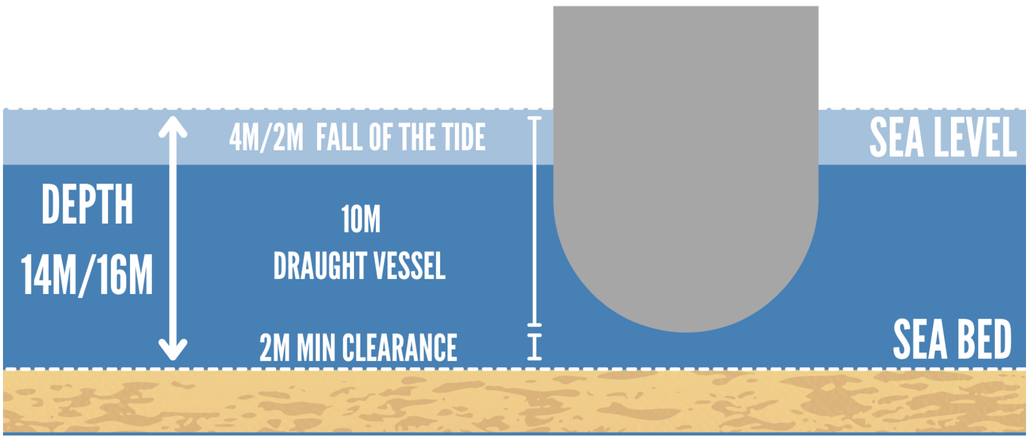
Notes: Kernel distribution of female-male ratios in 1801 (left) and 1811 (right). Dashed lines: cells below median recruits per capita; solid lines: cells above median recruits per capita. Kernel: Epanechnikov, bandwidth: 0.01.

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



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

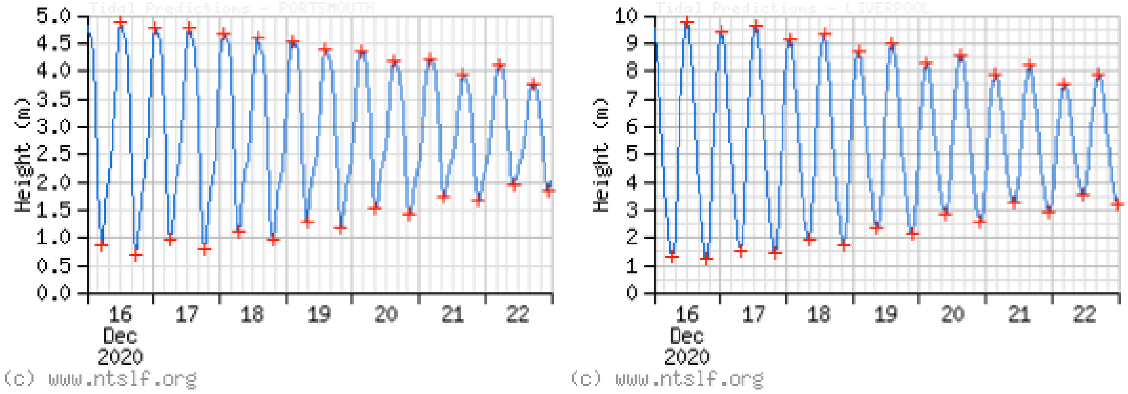
Figure A.4: Depth requirement for safe anchorage.



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

Figure A.5: Tides in Portsmouth and Liverpool

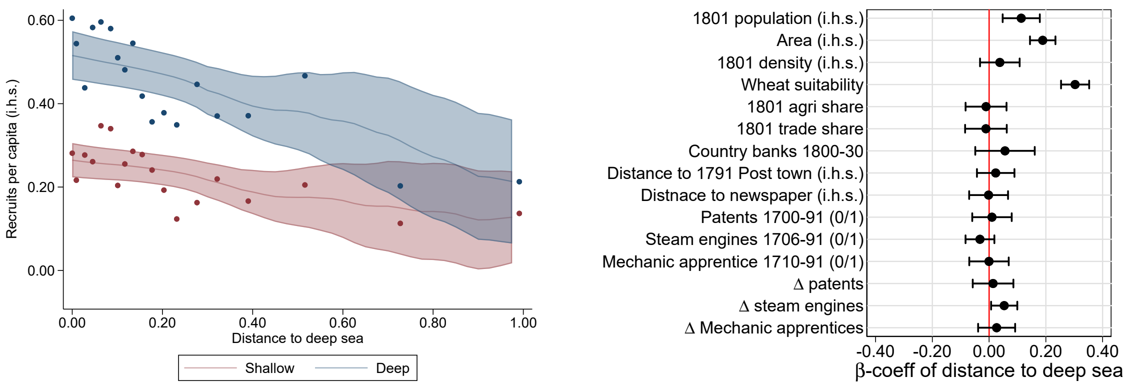
A. Portsmouth | B. Liverpool



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

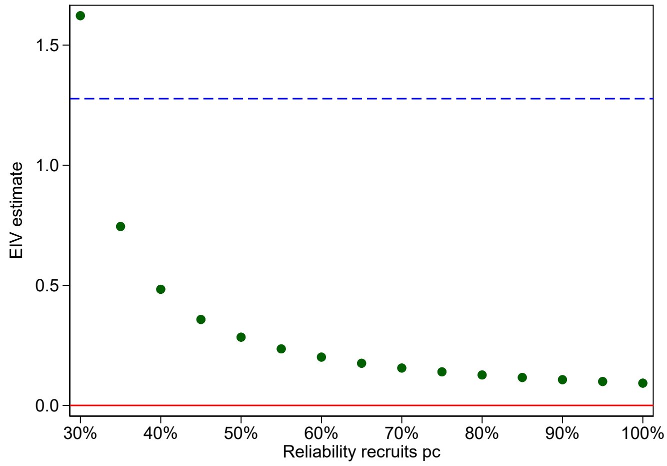
Figure A.6: IV strategy validation

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 plot unconditional binscatters of distance to the deep sea (x-axis) on Royal Navy recruits per capita (i.h.s., y-axis). We split recruits into those on deep (>5m depth of hold) ships (in blue) and those sailing on shallow (<5m) ships (red). 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.

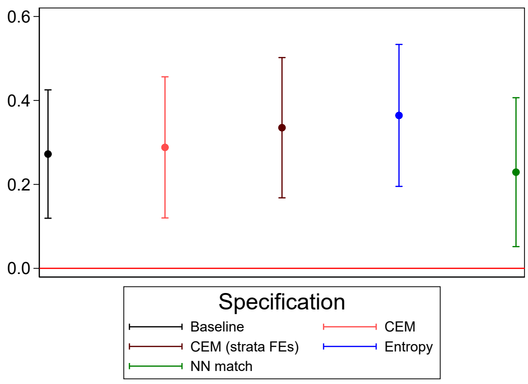
Figure A.7: Error in variables estimates



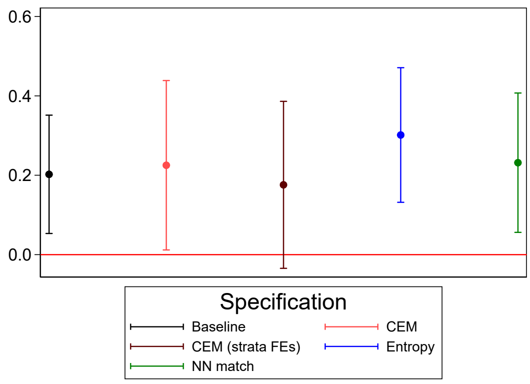
Notes: Error in variable estimates. The figure plots OLS estimates of the impact of naval recruitment on labor saving machine adoption (y-axis) against different levels of assumed reliability of the naval recruitment variable. The point at 100% reliability corresponds to the baseline OLS estimates, which 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

A. Controls



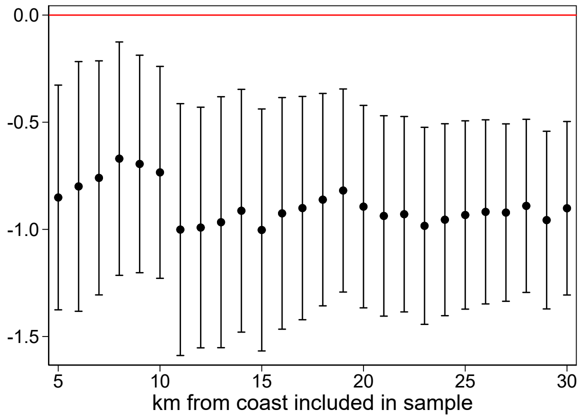
B. Controls & FEs



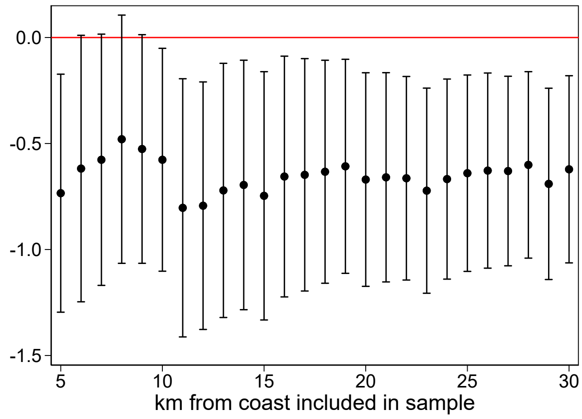
Notes: Coefficients and 95% confidence intervals of the effect of total military recruitment on labor saving machine adoption with different estimation methods. In each panel, from left to right, estimation method is: OLS (baseline); Coarsened Exact Matching (CEM: Iacus et al., 2012); CEM with strata fixed effects; weighted OLS with entropy weights (Hainmueller, 2012); and nearest neighbor matching. Panel A: specifications with all control. Panel B: specifications with controls and five region fixed effects. See Section 4.2 for details.

Figure A.9: Alternative definitions of coastal sample

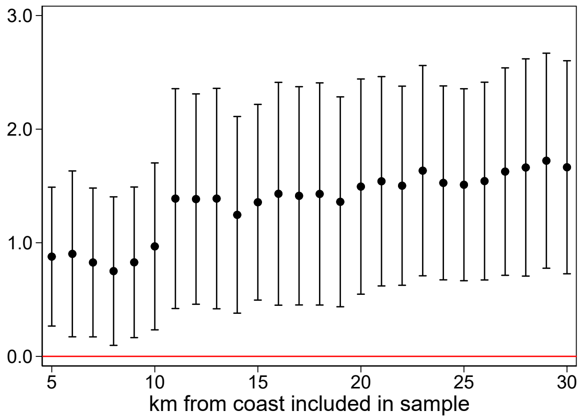
A. Reduced form, controls



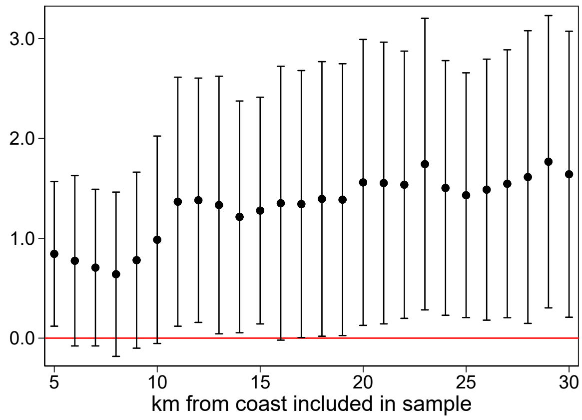
B. Reduced form, controls & FEs



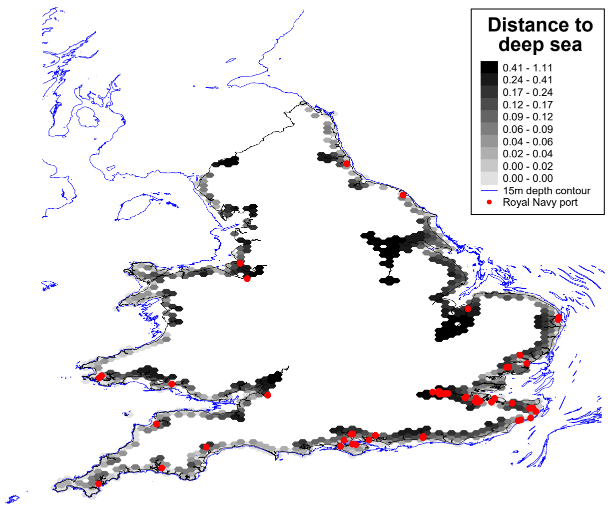
C. IV, controls



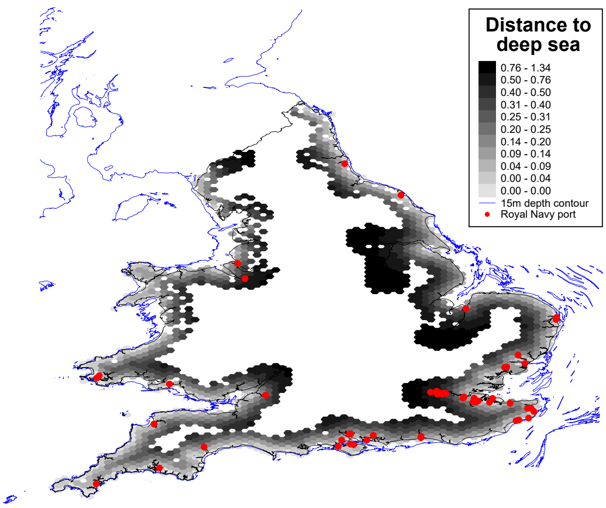
D. IV, controls & FEs



E. Coastal sample: 5km



F. Coastal sample: 30km



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.

C Appendix tables

Table A.1: Gender imbalances and recruitment

	Female - male ratio (i.h.s.)					
	(1)	(2)	(3)	(4)	(5)	(6)
	1801	1801	1801	1811	1811	1811
Total recruits p.c. (i.h.s.)	0.011***	0.005***	0.006***	0.016***	0.009***	0.010***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.002]	[0.002]
Demographic and geographic controls	No	Yes	Yes	No	Yes	Yes
Technology, skills and finance	No	Yes	Yes	No	Yes	Yes
Region FEs (5)	No	No	Yes	No	No	Yes
R^2	0.020	0.112	0.140	0.057	0.139	0.162
Mean dep var	0.906	0.906	0.906	0.912	0.912	0.912
Observations	2603	2603	2603	2473	2473	2473

Notes: OLS estimates. Dependent variable is female to male ratios (i.h.s.). 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	
	(1)	(2)
	Royal Navy	Commercial
Distance to deep sea	-0.082***	-0.026
	[0.030]	[0.075]
Distance to coast	Yes	Yes
Demographic and geographic controls	Yes	Yes
Technology, skills and finance	Yes	Yes
Region FEs (5)	Yes	Yes
R^2	0.190	0.298
Mean dep. var.	0.095	0.460
Observations	886	886

Notes: β coefficients from OLS estimates. Dependent variable is an indicator for port presence within 8 Km from the cell centroid. Col 1: ports are used by Royal Navy ships. Col 2: 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.

	Recruits p.c. (i.h.s.)			
	(1)	(2)	(3)	(4)
	Shallow hold	Deep hold	Shallow hold	Deep hold
Distance to deep sea	-0.156***	-0.343***	-0.155***	-0.256***
	[0.060]	[0.081]	[0.060]	[0.086]
Demographic and geographic controls	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes
R^2	0.166	0.214	0.170	0.239
Mean dep. var.	0.230	0.453	0.230	0.453
p-value deep = shallow		0.005		0.183
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: OLS-IV weights decomposition

	Coefficients			Decomposition		
Specification	OLS	IV	OLS - IV	Cov-Weights	Treat-Weight	Endogeneity
Controls	0.105	1.357	1.251***	0.027	0.016	1.209***
	(0.059)	(0.439)	(0.426)	(0.055)	(0.050)	(0.427)
Controls & Region FEs	0.106	1.277	1.171**	-0.018	-0.020	1.209**
	(0.063)	(0.579)	(0.568)	(0.072)	(0.067)	(0.578)

Notes: Decomposion of OLS–IV difference. First row: specification with all controls. Second row: specification with all controls and five region fixed effects. Col 1 reports OLS estimates of the effect of naval recruitment on labor saving machine adoption in the coastal sample. Col 2 reports IV estimates in the same sample. Col 3 reports the OLS-IV difference. The last three columns apply Ishimaru (2022) method to decompose this difference into three components: the ones stemming from different weights created by covariates (col 4) and treatment assignment (col 5) plus the residual difference (col 6, labelled "endogeneity"). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5: Analysis of compliers

	Average				p-value	
	Coastal Sample	Compliers	Always Takers	Never Takers		
	(1)	(2)	(3)	(4)	(2) - (3)	(2) - (4)
Distance to coast	0.040	0.052	0.059	0.017	0.616	0.000
	(0.002)	(0.011)	(0.004)	(0.002)		
1801 population (ihs)	7.876	8.043	8.222	7.456	0.376	0.002
	(0.028)	(0.165)	(0.059)	(0.073)		
Area (ihs)	5.324	5.477	5.443	5.137	0.620	0.000
	(0.012)	(0.075)	(0.009)	(0.038)		
Wheat suitability	3743.460	3792.995	3848.155	3616.899	0.526	0.046
	(13.636)	(76.360)	(20.061)	(33.633)		
1801 % agri workers	0.353	0.301	0.318	0.413	0.684	0.018
	(0.007)	(0.040)	(0.013)	(0.016)		
1801 % trade workers	0.109	0.102	0.126	0.094	0.282	0.670
	(0.003)	(0.018)	(0.007)	(0.008)		
Distance to 1791 post town (ihs)	2.930	2.950	2.723	3.129	0.112	0.194
	(0.022)	(0.120)	(0.049)	(0.042)		
Distance to newspaper town (ihs)	3.688	3.780	3.571	3.763	0.122	0.894
	(0.021)	(0.118)	(0.049)	(0.040)		
1800-30 country banks	0.304	0.269	0.575	0.049	0.246	0.216
	(0.033)	(0.187)	(0.106)	(0.029)		
1707-90 steam engines (0/1)	0.056	0.012	0.061	0.071	0.364	0.290
	(0.008)	(0.045)	(0.017)	(0.019)		
1700-90 patents (0/1)	0.060	-0.031	0.122	0.038	0.008	0.180
	(0.008)	(0.051)	(0.024)	(0.014)		
1710-92 mechanic apprentice (0/1)	0.395	0.373	0.552	0.247	0.124	0.256
	(0.016)	(0.091)	(0.036)	(0.032)		
Army recruits pc (ihs)	0.560	0.464	0.830	0.333	0.076	0.424
	(0.027)	(0.153)	(0.070)	(0.047)		
Proportions	1.00	0.183	0.409	0.408		
		(0.033)	(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: Extensive margin: linear probability model, probit and logit.

	Labor saving machines (0/1)					
	(1)	(2)	(3)	(4)	(5)	(6)
	LPM	LPM	Probit	Probit	Logit	Logit
Total recruits p.c. (i.h.s.)	0.051***	0.041***	0.175***	0.152***	0.296***	0.256***
	[0.009]	[0.009]	[0.029]	[0.030]	[0.049]	[0.053]
R^2	0.115	0.162				
Mean. dep. var.	0.290	0.290	0.290	0.290	0.290	0.290
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes
Marginal effect at mean recruitment			0.054***	0.045***	0.054***	0.045***
			(0.009)	(0.009)	(0.009)	(0.009)
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.7: Discrete choice models: Poisson and negative binomial.

	Labor saving machines					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Poisson	Poisson	Neg Bin	Neg Bin
Total recruits p.c. (i.h.s.)	0.210***	0.167***	0.281***	0.227***	0.295***	0.242***
	[0.045]	[0.043]	[0.047]	[0.048]	[0.052]	[0.047]
R^2	0.076	0.129				
Mean. dep. var.	0.786	0.786	0.786	0.786	0.786	0.786
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes
Marginal effect at mean recruitment			0.204***	0.166***	0.208***	0.177***
			(0.033)	(0.034)	(0.035)	(0.032)
Observations	2603	2603	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: Poisson regression. Cols 5–6: negative binomial regression. 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.8: Spatial standard errors

Panel A: Moran's I

Dep. var.: Recruitment	Labor saving machines Total		Naval	
Cutoff: 50 km	0.000	0.000	0.000	0.000
Cutoff: 100 km	0.000	0.000	0.000	0.000
Cutoff: 200 km	0.000	0.000	0.000	0.000
Cutoff: 400 km	0.000	0.001	0.000	0.010
Cutoff: 600 km	0.299	0.122	0.254	0.100
Demographic and geographic controls	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes
Observations	2603	2603	2603	2603

Panel B: Spatial standard errors

	Labor saving machines	
Indep. var.: Recruits (Army & Navy)	0.210	0.167
Robust s.e.	(0.045)***	(0.043)***
Conley s.e.: 50 km	(0.070)***	(0.058)***
Conley s.e.: 100 km	(0.077)***	(0.057)***
Conley s.e.: 200 km	(0.074)***	(0.051)***
Conley s.e.: 400 km	(0.059)***	(0.040)***
Conley s.e.: 600 km	(0.048)***	(0.032)***
Cluster: county	(0.080)***	(0.060)***
Indep. var.: Royal Navy Recruits	0.167	0.108
Robust s.e.	(0.049)***	(0.048)**
Conley s.e.: 50 km	(0.054)***	(0.046)**
Conley s.e.: 100 km	(0.054)***	(0.037)***
Conley s.e.: 200 km	(0.049)***	(0.031)***
Conley s.e.: 400 km	(0.037)***	(0.022)***
Conley s.e.: 600 km	(0.030)***	(0.018)***
Cluster: county	(0.053)***	(0.035)***
Demographic and geographic controls	Yes	Yes
Technology, skills and finance	Yes	Yes
Region FEs (5)	No	Yes
Observations	2603	2603

Notes: Robustness to spatial autocorrelation. Panel A: 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. Cols 1—2: military recruitment is army and navy recruits per capita (i.h.s.). Cols 3—4: military recruitment is navy recruits per capita (i.h.s.). Col 1 includes all controls. Col 2 includes all controls and five region fixed effects. Panel B: correction for spatial correlation with the formula of Conley (1999). Point estimates from Table 1 (cols 3–5). 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 2603 equally sized hexagonal cells. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: Robustness to including urban areas.

	Machines				Navy recruits		Machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Total recruits p.c. (i.h.s.)	0.205***	0.162***								
	[0.043]	[0.041]								
Royal Navy recruits p.c. (i.h.s.)			0.167***	0.105**					1.427***	1.603**
			[0.047]	[0.046]					[0.457]	[0.698]
Distance to deep sea					-0.690***	-0.506***	-0.985***	-0.812***		
					[0.119]	[0.129]	[0.273]	[0.289]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.072	0.124	0.068	0.120	0.352	0.373	0.105	0.133	-0.271	-0.322
Mean dep var	0.785	0.785	0.785	0.785	1.105	1.105	0.887	0.887	0.887	0.887
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: Royal Navy recruits per capita (i.h.s.). 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.10: Robustness **to** including areas far from a newspaper.

	Machines				Navy recruits		Machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Total recruits p.c. (i.h.s.)	0.219***	0.167***								
	[0.044]	[0.042]								
Royal Navy recruits p.c. (i.h.s.)			0.164***	0.097**					1.591***	1.521**
			[0.048]	[0.048]					[0.520]	[0.694]
Distance to deep sea					-0.747***	-0.590***	-1.189***	-0.897**		
					[0.117]	[0.129]	[0.339]	[0.354]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.075	0.136	0.070	0.132	0.303	0.332	0.097	0.152	-0.190	-0.100
Mean dep var	0.782	0.782	0.782	0.782	0.949	0.949	0.939	0.939	0.939	0.939
Observations	2899	2899	2899	2899	1054	1054	1054	1054	1054	1054

Notes: Robustness: sample includes cells further than 50 km from a city that publishes at least 1 newspaper as well as cells covering parishes never mentioned on 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: Royal Navy recruits per capita (i.h.s.). Units of observation are: cols 1–4: 2899 equally sized hexagonal cells; cols 5–10: 1054 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.11: Robustness to excluding areas close to victualling centers.

	Machines				Navy recruits		Machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Total recruits p.c. (i.h.s.)	0.220***	0.176***								
	[0.046]	[0.044]								
Royal Navy recruits p.c. (i.h.s.)			0.179***	0.119**					1.424***	1.344**
			[0.050]	[0.050]					[0.467]	[0.603]
Distance to deep sea					-0.725***	-0.582***	-1.032***	-0.782**		
					[0.120]	[0.132]	[0.298]	[0.307]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.078	0.132	0.073	0.128	0.292	0.318	0.113	0.147	-0.215	-0.121
Mean dep var	0.789	0.789	0.789	0.789	0.987	0.987	0.901	0.901	0.901	0.901
Observations	2544	2544	2544	2544	830	830	830	830	830	830

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: Royal Navy recruits per capita (i.h.s.). 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.12: Robustness to excluding Wales.

	Machines				Navy recruits		Machines			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS	OLS	OLS	FS	FS	RF	RF	2SLS	2SLS
Total recruits p.c. (i.h.s.)	0.215***	0.176***								
	[0.050]	[0.048]								
Royal Navy recruits p.c. (i.h.s.)			0.170***	0.112**					1.688***	1.781**
			[0.054]	[0.054]					[0.519]	[0.815]
Distance to deep sea					-0.708***	-0.496***	-1.195***	-0.884***		
					[0.121]	[0.133]	[0.315]	[0.333]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.071	0.124	0.067	0.120	0.288	0.308	0.105	0.129	-0.347	-0.350
Mean dep var	0.849	0.849	0.849	0.849	1.043	1.043	0.986	0.986	0.986	0.986
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: Royal Navy recruits per capita (i.h.s.). 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.13: Alternative measure of recruitment: recruits per men.

	Lab sav machines				Navy recruits p.m.		Lab sav machines	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	FS	FS	IV	IV
Army and Navy recruits per 1000 men (i.h.s.)	0.168***	0.132***						
	[0.034]	[0.033]						
Royal Navy recruits per 1000 men (i.h.s.)			0.132***	0.084**			1.029***	0.969**
			[0.037]	[0.037]			[0.330]	[0.437]
Distance to deep sea					-0.975***	-0.771***		
					[0.153]	[0.171]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.076	0.129	0.072	0.125	0.293	0.321	-0.169	-0.087
Mean dep var	0.786	0.786	0.786	0.786	1.385	1.385	0.887	0.887
Observations	2603	2603	2603	2603	886	886	886	886

Notes: Robustness: recruitment is measured in recruits per 1801 men (i.h.s.). 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: Royal Navy recruits per men (i.h.s.). 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.14: Alternative measure of adoption: threshing machines.

	Threshers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	RF	RF	2SLS	2SLS
Total recruits p.c. (i.h.s.)	0.101***	0.080***						
	[0.020]	[0.020]						
Royal Navy recruits p.c. (i.h.s.)			0.119***	0.087***			0.814***	0.721**
			[0.024]	[0.025]			[0.228]	[0.300]
Distance to deep sea					-0.602***	-0.422***		
					[0.146]	[0.153]		
Distance to coast	No	No	No	No	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology, skills and finance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.082	0.126	0.082	0.125	0.134	0.159	-0.261	-0.133
Mean dep var	0.460	0.460	0.460	0.460	0.579	0.579	0.579	0.579
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.