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

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Abstract

We establish a link between labor scarcity and the adoption of labor-saving technology in industrializing England. During the Napoleonic Wars, more than 10% of the male population served in the armed forces. Where recruitment was heavy, more machines economizing on labor were adopted. Naval recruitment, instrumented by warships' coastal access, provides exogenous variation in labor scarcity and suggests that the link between labor shortages and adoption is causal. Where mechanical skills were abundant, the impact of labor scarcity on adoption appears to be larger.

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

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

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

In this paper, we examine the determinants of technological progress during the British Industrial Revolution, offering a unified perspective that assigns a role to both labor scarcity and human capital. We do so by collecting and analysing new data on military recruitment and labor scarcity, wage pressure, technology adoption, and skill availability. New technology can only influence productivity if it is adopted. To measure technological change, we collect new, granular data on the diffusion of technologies, including labor-saving ones, in England. Our setting exploits a large shock to labor markets: The French Revolutionary and Napoleonic Wars (1793–1815) saw a rapid expansion of Britain's armed forces. Consequently, in many locations, the number of men dwindled. This is reflected in skewed sex ratios, indicating labor market imbalances. Wages in affected locations surged, as we

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

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

document with newly-assembled data on rural labor payments. Crucially, military recruitment went hand-in-hand with the adoption of labor-saving technology—but not of non-labor saving technology.[3]

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. While other studies of factor-scarcity induced technological change have emphasized the direction of invention, we focus on adoption. We present results using both army and naval recruitment, but exploit naval recruitment for identification. Contemporary accounts noted that coastal districts often saw both heavy recruitment by the Royal Navy and rapid adoption of labor-saving machinery. Recruitment was heavily decentralized, and was sometimes carried out by press-gangs which compelled individuals to serve involuntarily (Rodger, 2006).[4] Data from ships' muster rolls show that many "landsmen" (recruits without maritime experience) were recruited. What mattered for recruitment intensity was proximity to suitable anchorage. We instrument the number of men taken from any one location with the distance to the nearest offshore location accessible by large Royal Navy ships (which accounted for a large share of recruitment). Newly collected data from Royal Navy muster rolls documents the extent and geography of (involuntary) recruitment from rural areas. Within the set of coastal locations, places close to anchoring spots suitable for large warships saw heavier recruitment and faster adoption of labor-saving machinery. Contemporary commentary highlights the importance of naval labor demand for local labor markets. The effect is independent of proximity to the coast: for the IV analysis we consider only coastal areas and always control for direct distance to the coast.

We also document an important role for human capital: where labor shortages coincided with local mechanical skills, technology adoption was more rapid, similar to the recent work by Kelly et al. (2022). A combination of labor shortages and mechanical skills may have facilitated technological progress. We create an indicator of local mechanical knowledge, combining data on apprenticeships (to measure local skill supply), patenting (local expertise in advancing the knowledge frontier), and the use of terms indicative of technology adoption. In locations where more young men trained as blacksmiths, watchmakers, and millwrights, and where inventors patented new mechanical machines, the impact of the Napoleonic Wars on technol-

[3]The aggregate effect of recruitment on non-labor technology adoption is indistinguishable from zero, as is the effect of naval recruitment; any association with non–labor-saving technology is limited to army recruitment and is weak.

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

ogy adoption appears to be larger. 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 four newly-collected datasets. First, we assemble a comprehensive individual-level database of naval and army recruitment in England during the Napoleonic Wars, combining existing army enlistment data (Floud et al., 1990) and hand-collected muster rolls for the navy. At their peak the army and navy had an estimated 350,000 men under arms. The British Army recruited across the country. The Royal Navy grew from 16,000 men in 1792 to nearly ten times that number in 1812. We collect a large sample of ships' muster-rolls from the archives (National Archives, nd). These data allow us to measure local labor market shocks due to naval recruitment.

Our second new dataset measures the adoption of both labor-saving and non-labor saving machines. We use granular data on the adoption of ten technologies over the period 1790–1820 in over 10,000 English parishes, using information from historical newspapers. Based on historical 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 combines information from government surveys of agricultural conditions in each county (the *General Views* series, Young, 1817) and other sources. We examine over 20,000 pages, extracting wage rates at different points in the agricultural year, during the Napoleonic Wars. These show not just the general rise in wages—in line with aggregate trends—but also local variation. In particular, they demonstrate recruitment-induced labor shortages during the Napoleonic Wars translated into wage pressure.

The fourth 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, awarding prizes to the best designs. We show that machines were more productive in areas where wartime recruitment had promoted early technology adoption, suggesting that the (temporary, but long-lasting) shock to labor supply during the Napoleonic Wars had far-reaching consequences. We also find that structural change—the movement of the labor force out of agriculture—was more rapid in areas of labor-saving technology adoption.

Our results are robust to a wide range of alternative approaches. Discrete choice models (Probit, Poisson) to explain the extensive margin of adoption yield similar results, and the significance of our effects is not undermined when we correct for

potential correlation of spatial errors with clustering, Conley standard errors, or t-statistic based inference (Ibragimov and Müller, 2010). We also show that the effect of naval recruitment on technology adoption does not reflect exposure to commercial port activity, or to a more active land market. Finally, we examine whether possible limitations of our main source for adoption—newspapers—might be driving results, and find no evidence for this notion.

By linking the adoption of labor saving technology to labor scarcity, our findings provide empirical support to theories of directed technical change (Hicks, 1932; Habakkuk, 1962; Acemoglu, 2002, 2003, and 2007). These models clarify under what conditions labor scarcity promotes innovation, and highlight the importance of technologies' factor bias: only (strongly) labor saving technologies benefit from labor scarcity. Several papers bear out this prediction: Hanlon (2015) shows that 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).[5] Franck (2022) finds ambiguous effects of labor shortages on technology adoption in 19th century France, while Dower and Markevich (2018) conclude that Russian mobilization in 1914–17 reduced land under cultivation, instead of spurring mechanization. Arguably, British agriculture responded to labor shortages with labor-saving technologies because it operated under fewer distortions. 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.[6]

Our paper also contributes to debates on the origins of the British Industrial Revolution. Economic historians have highlighted several factors that made 17$^{\text{th}}$ and 18$^{\text{th}}$ century Britain special, including institutions (North and Weingast, 1989), overseas colonies (Inikori, 2002), culture and psychology (McCloskey, 2010), slave wealth

[5]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.

[6]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.

(Heblich et al., 2022), natural resources (Wrigley, 2010) and chance (Crafts, 1985). While literacy rates were low (Mitch, 2004), Britain had an unusually large number of highly skilled mechanics: workers who had acquired significant non-codifiable knowledge through on-the-job training (apprenticeships) and were able to introduce a constant stream of micro-inventions and improvements to machines (Kelly et al., 2022).

We contribute to both the literature on directed technological change, and to research on the determinants of the Industrial Revolution. We provide well-identified evidence of a large, country-wide labor market shock accelerating technological progress during the British Industrial Revolution. By documenting the effect of labor scarcity and higher wages on technology adoption in agriculture, we show that the mechanism hypothesized by Allen (2009) applies country-wide, and outside the textile and metal sectors. In combination, our cross-sectional evidence confirms Allen's basic predictions and shows their relevance beyond the (relatively small) number of "leading sectors" of the Industrial Revolution. Where labor scarcity coincided with the presence of local trained mechanics (Mokyr, 2009), technology adoption accelerated—and so did the productivity of new machines. Earlier contributions in the literature on directed technological change have already demonstrated that factor scarcity can lead to new innovations (Hanlon, 2015; San, 2022; Lewis, 2011) and technology adoption (Hornbeck and Naidu, 2014). Importantly, we demonstrate for a canonical case that there is a synergy between labor scarcity and skill abundance in driving automation—a mechanism predicted in theory (Hémous and Olsen, 2022; Krusell et al., 2000), but with limited empirical support. Skill abundance and labor scarcity jointly spurred automation, and that automation in turn generated new skilled tasks related to installing and operating machinery, suggestive of "reinstating" technology change in recent theoretical contributions (Acemoglu and Restrepo, 2018). In combination, these findings suggests a unified interpretation of the British Industrial Revolution, with factor scarcity leading to directed technological change, facilitated by readily available human capital.

1 Historical Background

At the height of the Napoleonic Wars, in 1812, an official agricultural survey for Dorset, the *General Views of Agriculture*, 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. (Young, 1813, p. 144)*

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

1.1 The First Industrial Nation

Britain had relatively high wages, productivity, and per capita income on the eve of the Industrial Revolution (Allen, 2009), rivaled only by the Netherlands. Wages were particularly high relative to the cost of energy (Allen, 2009). Total real GDP growth during the Industrial Revolution was relatively slow—1.2% p.a. in the second half of the 18th century, rising to 1.7 to 2.3 % in the next 50 years. Real per capita income growth was in the 0.3-0.9% range. While total factor productivity grew by less than half a percent during the 70 years after 1760 (Broadberry et al., 2015), the fact that there was an increase—and no collapse—is remarkable. To achieve sustained growth in per capita output while population grew rapidly signalled a decisive break away from Malthusian fetters (Crafts and Mills, 2020).

New technology was an important driver of these output and efficiency gains. Inventions do not spell productivity gains on their own; without a string of 'micro-inventions' that turn an idea into useful machinery, there can be no economic impact (Mokyr, 1992). Technology adoption, in this sense, is as valid a measure of technological progress as, say, patents.

Structural change was a dramatic feature of Britain's industrialization. Almost every country on the eve of industrial take-off had a substantial productivity deficit in agriculture (Crafts, 1985). In contrast, in Britain output and employment shares in agriculture were both equal to 31% as early as 1801 (Broadberry et al., 2015). Britain thus "released" surplus labor from agriculture long before other countries.[7] In 1759, industry already employed more than a third of the labor force, rising to half a century later.

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 centered on large commercial farms, in contrast to continental, peasant-based subsistence farming (Wrigley, 1985; Dower and Markevich, 2018). New methods such

[7]The 'release' took the form of agricultural employment not keeping up with the rise in aggregate population.

as crop rotations, fertilization, and drainage boosted productivity. Hired labor was key for operating large-scale, efficient farms. These included agricultural servants (on annual contracts) and day laborers (Kussmaul, 1990). During the early modern period, many laborers lost access to the village commons, making them reliant on wage income. Britain also operated a generous system of income support, the "Poor Law" (Boyer, 1990). Relief was reserved for those with a "settlement" in a parish (obtained by birth, marriage, or apprenticeship); to leave was to lose income support, and some contemporaries argued this discouraged mobility and reduced labor market integration. Adam Smith (1776, p.117) observed: "The very unequal price of labour which we frequently find in England, in places at no great distance from one another, is probably owing to [...] the law of settlements [...] The scarcity of hands in one parish, therefore, cannot always be relieved by their superabundance in another." Although recent research finds some labor migration (Hindle, 2004), it was clearly insufficient to equalize wages: Our new wage data confirms large differences between local labor markets, and the sex ratio evidence further suggests strong barriers to migration. The Poor Law thus reduced labor mobility. It was also a way for farmers to shift some of the cost of maintaining agricultural laborers on the general purse (Boyer, 1990). Thus, the existence and use of the Poor Law does not speak against labor scarcity and high labor costs in many parts of England.

Several new agricultural technologies emerged during the Industrial Revolution, many of them labor-saving. Threshing was labor-intensive, accounting for approximately half of all farm labor performed from November to March. The Scottish engineer Andrew Meikle invented the first threshing machine in the late 18$^{\text{th}}$ century. Originally powered by horses, these soon used water and, later, steam power (Caprettini and Voth, 2020). Initially, high costs and low reliability limited adoption to northern England, where agricultural wages were higher (Macdonald, 1975; Caird, 1852).

From the late 1790s onwards, adoption across Britain was rapid. Contemporaries knew that machines were spreading. For example, many of the early 1800 General Views (Young, 1817) document that threshing machines were becoming "more common every day" (Berkshire 1813; p.118); "general" (Cambridgeshire 1811; p.50; Cornwall 1811; p.43; Northumberland 1797); "very prevalent" (Devon 1808; p.121); and that they "made a rapid progress and are now almost in general use" (Durham 1810; p.80). These machines were "getting into much use" in Hampshire (1810; p.112) and their spread had "been considerable" in Derbyshire (1811; p.49); "few farms of consequence being now without them" in Cornwall (1811; p.43).[8] Mecha-

[8]Arthur Young surveyed Suffolk in 1797 and 1804 "[a]t the time of my drawing up the first

nization was also not confined to threshing machines, and other technologies spread fast too: to name but one, winnowing machines were "in pretty general use" in Somerset (1798; p.46); Dorset (1812; p.144); and Gloucestershire (1807), where they "seem likely, in a few years, to take entire place of the old winnowing-fan" (p.86). In short, the General Views indicate that English farmers were "alive to improvements, and ready to adopt any new instruments which promise utility" (Lincolnshire 1799; p.76).

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, as illustrated in this Poor Law return from Burnham, Buckinghamshire, from 1832:

> *Q. Do your farmers employ fewer hands than they did before those machines were introduced?*
>
> *A. Considerably. [...]*
>
> *Q. How soon after their introduction did they begin to employ fewer hands?*
>
> *A. Directly they began working them; instantly.*
>
> *Q. How many months will a threshing machine take to thresh out the produce of a farm which before took the men ten months?*
>
> *Q. They will thresh it out in two months."*

The new machines raised productivity fivefold and reduced labor demand (Caprettini and Voth, 2020); because the task required substantial physical strength, they also reduced the demand for prime-age men in favor of women and children.

Horse hoes that removed weeds and horse rakes allowed further labor savings: Fussell (1952, p.139) observes that before the horse rake "it needed nearly as many men to make hay as the blades of grass they gathered," and Long (1963) estimates that one horse rake could do the work of 20 men.[9] Mowers cut the stalks and reapers collected the grain, replacing some of the most labor intensive agricultural activities (David, 1966). Mowers diffused only after reapers did, and reaper technology was rudimentary for some time (Fussell, 1952). In contrast, turnip cutters, chaffing machines and cake crushers facilitated fodder production: cutting turnips, grinding chaff, and crushing the cake residue of oil manufacture. Before their introduction "there was little feed preparing" and "beasts had to survive as best they could"

edition of this Report, there was not ... one threshing mill in the county. They are now considerably multiplied" (Suffolk, p.34).

[9] Rahm (1844, p.254) finds that the horse hoe was invented because the hand hoe was not "sufficiently expeditious on a large scale."

(Fussell, 1952, p.180). They were adopted because they allowed to produce more fodder from the same produce; this used additional labor, instead of saving it.

1.3 Britain During The Napoleonic Wars

Britain was at war against revolutionary France and then Napoleon from 1793 to 1815, except during the brief Peace of Amiens (1802–03). Napoleonic France conquered most of continental Europe, while the United Kingdom seized most French colonies and those of her allies. The UK relied on a large fleet to support its allies, conduct amphibious landings, cut France and her allies off from her colonies, and blockade trade routes. War was the single most expensive activity an early modern state could engage in, and its cost regularly outstripped revenues from ordinary taxation. Britain financed its wars mostly through borrowing (Brewer, 1988). By 1815, Britain's debt-to-GNP ratio exceeded 200%.

After 1792, Britain's armed forces expanded rapidly. Before the outbreak of war, the Royal Navy had numbered around 16,000 sailors; at its peak in 1812, it had grown tenfold, to around 150,000 men and almost 1,000 ships (Rodger, 2006). The British Army reached a peak of 200,000 men in 1813. After 1815, both branches shrank: by 1821, the navy's size had declined to only 14,000 men, while the army was down to 110,000 (Clowes, 1899; Fortescue, 1899). In combination, the British armed forces counted more than 350,000 men under arms at the moment of greatest mobilization (1813). This is equivalent to 10–14% of the adult male labor force in Great Britain at the time (Wrigley and Schofield, 1981).[10]

Nonetheless, even these peak time numbers underestimate the full impact of recruitment. Assembling and maintaining such massive armed forces resulted in a major labor market shock. Combat losses were relatively low, but illness took a substantial toll. Overall British casualties amounted to 310,000 for the period 1804–1815 alone—90,000 for the Royal Navy and 220,000 for the British Army (Dumas and Vedel-Petersen, 1923). In the face of such losses, maintaining armed forces equivalent to 10-14% of the adult male population required a steady influx from the civilian labor pool.

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

[10]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. Rodger (2006, p. 501) estimates that British recruitment was three times that of France, relative to the country's population.

contributed to rural labor shortages. Naval recruitment created additional pressures on the civilian labor market. Some recruits came from abroad (Dancy, 2018), but the vast majority were British. The navy preferred able seamen and sought to recruit merchant sailors. However, "...when there had been a long peace. ...[e]xpansion of the total seafaring population to a new level of demand took time... *the main increase had always to be achieved by persuading large numbers of untrained landsmen to go to sea.*" (Stewart, 1960, our emphasis). The press was a common way to 'persuade'. Most recruitment happened through the Impress Service, which maintained offices (*rendezvous*) throughout the country. Individual captains, which historically had to man their own ship, continued to recruit on their own, but came to depend more on central recruitment (Dancy, 2018). Almost all Impress Service offices were located to ensure easy access to the deep sea, allowing large navy vessels to take newly recruited hands aboard. The same geographical logic governed the recruitment activities of individual captains. Recruiting new sailors created indirect pressure on the local labor market, including for those employed in non-seafaring activities. Direct pressure came from the recruitment of landsmen: as many as 108,000 prime-aged Englishmen without prior maritime training may have been recruited during the Napoleonic Wars.[11] During the mid-1700 pressing landsmen was rare and legally problematic (Rodger, 1986), but the enormous manpower pressure of the war induced the Cabinet to authorize the forcible recruitment of landsmen (Morning Post, 5 July 1803, reported in Appendix Figure A.1). Indeed, during periods of "hot press," in times of major military recruitment crises, all legal safeguards were suspended—an occurrence so common that the phrase was used as simple shorthand for general press-ganging in British newspapers at the time. Muster rolls data allows us to examine the share of landsmen marked "Prest", suggesting a figure at least 13% of landsmen were pressed in 1800—15 (see Appendix Figure A.1 for examples), and many more may have been "encouraged" by the press to "volunteer" (and thus to receive a signing bonus).[12] A systematic analysis of newspaper articles published in 1790–1820 documents at least 88 separate episodes of "hot press" that forcibly recruited landsmen (Appendix Figure A.2). Since both the navy and

[11]We find a 21% share of landsmen in our sample of seamen. Landsmen graduated to ordinary seamen in 2–3 years. A constant share of landsmen implies that this group was constantly replenished. If each landsman kept his rating for 3 years, the Navy had to replace one-third of them p.a. This implies an intake of 197,000 landsmen in the Navy between 1792 and 1815. As 55% of landsmen came from England and Wales (Dancy, 2018, p. 52), some 108,000 landsmen joined the Royal Navy during the years of the wars against France.

[12]Note that our analysis of ships' muster rolls is the most comprehensive one undertaken to date, by a factor of more than 3—as Figure A.3 shows, we use a total of 95,012 individual seamen records from 264 ships, whereas Dancy (2018) drew on 27,174 records from 81 ships).

the merchant marine expanded in terms of manpower (Dancy, 2018, reproduced in Figure A.4), coastal districts experienced sharp increases in labor demand. Our IV strategy exploits geographical determinants of naval recruitment to estimate causal effects.

2 Data

We assemble five new datasets to test the impact of labor scarcity on technology adoption during the British Industrial Revolution. First, we compile representative database of military recruitment from both British Army and Royal Navy sources. Army data come from Floud et al. (1990), covering 23,749 soldiers enlisted 1790–1819. For the Navy, we digitize muster rolls from 264 ships (1793–1815), yielding 95,012 sailor records from three sources: the Battle of Trafalgar project, Dancy (2018), and our own collection (cf. Appendix Figure A.3, which depicts our sample as more than trebling that previously used). We geolocate the origins of over 45,000 of these recruits from the army and navy across England and Wales, providing granular measures of wartime labor market shocks (Figure 1-Panels A, B).

Second, we track technology adoption through historical newspaper advertisements (British Library and Findmypast, 2022), building on Caprettini and Voth (2020). When farms were sold, machines were listed in sale notices. We identify 4,875 agricultural machines in 1790–1830—3,878 labor-saving and 997 non-labor saving—using functionality descriptions from Fussell (1952). We take care to not double-count them. This covers threshers, horse rakes, mowers, reapers, turnip cutters, and chaffing machines across 10,000 parishes. We use the number of machines advertised in 1790-1820 as our main dependent variable (Figure 1-Panel C and D). Since we observe adoption with a lag due to the logic of purchasing and subsequent sales, these machines were almost all purchased before the end of the Napoleonic Wars.

Third, we extract wage data from several historical sources. Using LLM-assisted analysis of over 20,000 pages from the *General Views of Agriculture* (Young, 1817), Eden (1797) *State of the Poor*, and Arthur Young's 1770s *Tours* as summarized by Rogers (1902), we exploit more than 1,500 wage observations spanning 1770-1811. This captures both pre-war and wartime labor market conditions.

Fourth, we measure technological progress through Royal Agricultural Society competitions (1841–1872). Records contain productivity data for 306 threshing machines from RASE records (Brunt et al., 2012), allowing us to track performance improvements over time and space. Figure 2 shows productivity over time.

Fifth, we also compile a new measure of human capital, using five variables: a)

apprentices in mechanical trades (wheelwrights, clockmakers), 1792–1811, b) agricultural patents, 1792–1820, c) metallurgy patents, 1792–1820, d) metal goods patents, 1792–1820, e) mentions of words related to "mechanical knowledge" published in any British newspaper during the Napoleonic Wars between 1792 and 1820.

Detailed information on these variables and additional controls is provided in the Data Appendix (Appendix A). We aggregate all variables to 2,600 equally-sized hexagonal cells of 120 square kilometers covering England and Wales. Our main sample consists of 2,600 non-urban cells within 50 km from a town publishing one (or more) newspapers.

3 Main Empirical Results

This section examines the effect of military recruitment on technology adoption. We first show that recruitment led to local labor scarcities, as reflected in skewed sex ratios. This, in turn, led to higher wages. Labor scarcity strongly correlates with the adoption of labor-saving technologies, but not of non-labor saving technology. Our IV strategy identifies the causal effect of these labor shortages. Additionally, skill abundance amplified the effect of labor scarcity in promoting technology adoption. We find limited support for synergies with other, alternative drivers of industrial development.

3.1 Gender Imbalances and Wage Pressure

Did military recruitment lead to labor shortages? And did these in turn push up wages? We first show that where the army and navy recruited extensively, gender imbalances were greater. Then, we use newly collected data to show that labor shortages drove up wages.

Because gender ratios at birth are close to one, we can use local variation in the share of men and women in the population as an indicator of labor shortages. In areas with above-median recruitment, sex ratios were more skewed (Panel A–B of Figure 3). Table 1 examines the relationship between military recruitment and gender imbalances. Panel A shows that total recruitment pushed up the ratio of women to men, with or without fixed effects (col 1 and 2). The same is true for navy recruitment (Panel B, col 1 and 2). Effects are large: the β-coefficients reported in the table indicate that one standard deviation (s.d.) in log total (Navy) recruitment increases log gender ratios by 0.13 (0.15) of a s.d. Thus military recruitment correlates with higher shares of "missing men," arguably because they were away, fighting for Britain.

What were the effects of recruitment on local labor markets? The *General Views*

report that the "increase of the price of labour is owing in some measure to the scarcity of hands" (Lincolnshire, 1799) and that "farmers not only complain of the rapid advance of wages, but of the difficulty of procuring steady and deserving labourers" (Cambridgeshire, 1811). The Earl of Hardwick in 1797 "could have no men but at high wages" (Jones, 1964, p.324). In Yorkshire, wage increases were "more from the great consumption of men in the navy and army, and consequent present extreme scarcity of hands for agricultural labour." In Suffolk, the General View notes the "effect which the [...] scarcities have had in raising the price of labour, united with that of military arrangements, has been very great indeed". Combined with the initial quote from Dorset, there is ample contemporary evidence of military-recruitment induced labor shortages driving up wages across Britain.

Our wage data confirm the assessments of early 19C experts. We use more than 1,500, newly collected, local wage rates to show that between 1790 and 1811, winter and summer wages increased by 103% and 104% respectively. During the same years, the Clark (2010) index of cost of living rose by 64% and wheat prices by 77%. Clearly, labor became markedly more expensive in absolute terms, and relative to a basket of other goods.

Table 1 shows regression results for the effect of Navy recruitment on wages (Appendix Figure A.5 illustrates the positive relationship with winter and summer wages using binscatters). Both general recruitment and naval recruitment in a location are associated with higher wages. This pattern holds true with and without fixed effects (col 3–4). Importantly, high recruitment areas had prior of the war *lower* wages (col. 5 and 6), suggesting that wartime recruitment significantly reshaped labor markets. Going from the 25th to the 75th percentile of naval recruitment pushed up winter (summer) wages by 0.8 (one) pence per day: between five and six percent of the average.

3.2 Machine Adoption: OLS Results

Do recruitment-induced labor shortages predict machine adoption? In Figure 4, we present binscatters of labor-saving and non-labor saving machines against military recruitment. For *labor-saving* machines (Panel A), there is a strong positive correlation with recruitment. The pattern is not evident for non-labor saving machines (Panel B). Similar patterns emerge when looking at adoption and women-to-men ratios (Appendix Figure A.6).

To go beyond the graphical evidence, we estimate:

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

The impact of military recruitment R in cell i on machine adoption M is captured by β. Our unit of observation i is one of 2,600 equally-sized cells covering the whole of England and Wales. X' is a vector of controls which includes other potentially important determinants of technology adoption. Demographic factors such as total population and the share employed in agriculture and trade in 1801 influenced the size of the agricultural sector and its demand for machines. Finance may affect farmers' ability to purchase new equipment. We measure access with the presence of country banks in 1791. Local technological expertise may also influence the introduction of new machines, as discussed in the data section.

We control for geographic factors, such as area, wheat suitability (Fischer et al., 2021), ruggedness (Nunn and Puga, 2012), access to fisheries (Dalgaard et al., 2020), proximity to a commercial port, and distance to the nearest post office town in 1791, which may influence machine profitability. Additionally, towns publishing newspapers likely serve as centers for diffusing new ideas, facilitating adoption in nearby areas. To address potential oversampling of areas covered by local papers (Beach and Hanlon, 2022), we control for the total number of farm ads, which are more numerous than machine ads (14,532 vs 2,723), and the distance to the nearest town with a newspaper. We also focus on the sample of cells within 50 km from a newspaper and covering at least one parish mentioned in the news. In the most conservative specification, we include five region fixed effects α_r to account for potentially varying labor market conditions across England, including e.g. different implementation of the Poor Laws and the law of settlement (Caird, 1852).[13]

Table 2 explores the basic patterns. Panel A reports estimates of beta coefficients for labor-saving machines. We find a large and highly significant association between per capita recruitment and labor-saving technology adoption across all specifications. This is true for the basic OLS specification (col 1), as well as for the expanded 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 army recruitment yields a somewhat larger coefficient. The data displays spatial dependence, but significance is not affected when we use the robust methods suggested by Conley (1999), Ibragimov and Müller (2010), and Conley and Kelly (2025). Subsection 5.3 discusses these results.

The effects are large. Our baseline result suggests that a one s.d. increase in

[13]We include log-transformed recruitment, population, and farm ads due to their skewed distributions. We assign -2 to cells with no recruitment to ensure observations with 0 receive the lowest value (Chen and Roth, 2023). As a dependent variable, the extensive margin is valued at 200 log points. We also demonstrate that our conclusions are robust to alternative assumptions (Appendix Tables A.39-A.40).

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

The adoption of non-labor saving machines is only weakly predicted by recruitment. Unconditional OLS estimates suggest a significant effect, but it is smaller—0.09 s.d. (Panel B, col 1). However, once we control for other variables, the coefficient becomes statistically insignificant and falls to zero (cols 2–4). There is no effect for the Royal Navy (col 5), but British Army recruitment had a positive and significant impact on the adoption of non-labor saving machines. However, the point estimate for army recruits is only half of the coefficient for labor-saving technology in Panel A. We reject the null of identical coefficients for labor vs non-labor saving machinery in all specifications ($p = 0.02$ or lower, reported at the bottom of the table). These results do not depend on working with the total number of machines: Appendix Table A.1 regresses log machines on recruitment and finds near-zero effect for non-labor saving machines. Military recruitment does not correlate with all types of technology adoption: war-induced labor shortages mostly led to the diffusion of machines built to save labor.

3.3 Machine Adoption: IV Results

The OLS results could be biased for several reasons. We observe only a fraction of total recruitment; large measurement error may introduce downward bias. Moreover, unobservable characteristics correlated with both recruitment and adoption may add further bias. For example, if recruitment efforts targeted non-agricultural workers outside rural areas, 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 present an IV strategy that exploits plausibly exogenous variation in recruitment.

We focus on Navy recruitment and instrument it by 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 5. We first discuss the logic of the instrument and then present several exercises supporting the validity of the strategy.

Intuition. Captains could recruit volunteers or pressed men. Deep sea access

allowed them to reach some areas more easily than others. In these areas, greater numbers of men joined the Navy—voluntarily or otherwise—because Royal Navy ships visited more often. We focus on geographic characteristics that facilitated Navy access, but that did not affect the local labor market otherwise.

Our instrument captures the ease with which Navy ships could reach the coast. Ships would anchor at sea, and then send in smaller boats—a cutter, gig, or a launch. They could only be used over short distances. Because most naval recruitment was carried out by ships much larger than civilian ships, we can separate military labor demand from that of the merchant marine. This avoids the concern that focusing on maritime districts may simply reflect trade effects. Our instrument is thus based on the technical characteristics of military ships in the Age of Sail. Ships of the line had a draft of around 7m and typically anchored at a minimum depth following the FUD rule (Appendix Figure A.7), translating to 10–15m for first-rate to third-rate ships, with an average of 12.5m.[14] Larger vessels accounted for the bulk of manpower used in the Royal Navy (Lavery, 2020).

To avoid confounding our effect with proximity to the sea, we restrict our sample to cells within 15km from the coast and control for distance to the coast directly. We then use distance to the deep sea, defined as the distance from the cell centroid to the closest point of the seabed 12.5m below the waterline (Figure 6-Panel A). In this coastal sample, the farther the 12.5m 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 12.5m affects adoption of agricultural machines only through its effect on naval recruitment.

To build intuition, consider two ancient parishes—North Ferriby and Lesbury in North-East England (in red and green in Appendix Figure A.9). Both lie on the North-East coast of England and have access to a small commercial port. In 1801 both were home to 900–1,100 people each, between one-quarter and one-fifth employed in agriculture; the share of workers in trade was 9–13 percent. Both cells scarcely had access to finance or advanced technology: until 1791, we find no country bank, no mechanic apprentice, no British inventor, and not a single Newcomen steam engine. However, the two parishes were different in one crucial dimension: Lesbury's coast opens directly onto the deep North Sea while North Ferriby lies on the shallow waters of the Humber river estuary, 39 km farther from the deep sea. The Royal

[14]We examined historical charts compiled by the Admiralty's Hydrographic Office, and compared them with modern-day measurements. Appendix Figure A.10 shows the high degree of similarity.

Navy recruited in Lesbury but not in North Ferriby, resulting in greater gender imbalances (1.21 vs 1.08 women per men) and faster technology adoption: we find four times as many labor saving machines in Lesbury (4 vs 1). Our IV strategy extends this comparison to the full sample of coastal cells.

Who was recruited in locations closer to the deep sea? Landsmen overall—sailors on Navy ships without prior seafaring experience—typically came from further inland than ordinary or able seamen. These served in the merchant marine or fisheries beforehand, and this often came from parishes close to the coast. The subset of landsmen registered as pressed, in contrast, came from areas closer to the deep sea (one-sided p-value = 0.08), as the logic of our IV-strategy predicts.

Validation. Our IV-strategy is plausible for four reasons. First, Table A.2 shows a strong, significant effect of distance to the deep sea on the location of Navy ports, with one s.d. in distance to deep sea reducing the likelihood of one being present by 0.7 s.d. The same is not true of commercial ports, where effects are weaker and quickly become insignificant. To identify the busiest ports, we digitize two years of data from Lloyd's List, tracking every ocean-going vessel sailing to or from a British port. The top 17 ports account for 96% of the country's traffic. Moreover, for seven of these ports, military ships contributed more than a quarter of all ships movements:[15] distance to these ports is significantly correlated with distance to the deep sea (Appendix Table A.2). Distance to deep sea predicts the presence of commercial ports, too, in the most basic specification; however, as we add controls, the relationship disappears.

Second, we predict the presence of Navy ports with distances to alternative sea depths, from 5m to 25m. Figure 6-Panel C plots the coefficients and confidence intervals from separate regressions that include all controls and distance to different bathymetric lines. We find a significant negative coefficient from the 7m contour line onwards, with the effect rising in magnitude and size up to the 16m line. This is consistent with the technical requirements of Royal Navy vessels, with some effect from medium depths for smaller ships like frigates, and much larger effects for 10-15m interval (note that frigates could easily anchor in 15m depth, but no first-rate could do so in 7m of depth). Distances to depth lines are highly correlated for each hexagon. We operationalize distance to the deep sea based on the 12.5m line.[16]

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 3-Panel A suggest a strong correlation between Royal Navy recruitment and deep sea: the closer an

[15]These are: Deal, Portsmouth, Plymouth, Falmouth, Yarmouth, Sheerness and Torbay.

[16]Results are essentially identical using the 10 and 15m line.

area is to deep, navigable sea, the higher the navy recruitment rate. In contrast, the Army was not constrained by distance to the deep sea; cols 3–4 of the same table confirm that distance to deep sea and army recruitment are unrelated (coefficients are significantly different from each other: $p \leq 0.006$). Thus, naval recruitment close to the deep sea was not compensated by reduced army recruitment.

We also partition naval recruitment based on the depth of ships' hold and ask whether distance to the deep sea mattered more for large ships.[17] Appendix Figure A.9 shows that the recruitment of seamen always declined with distance, but that the relationship is much stronger for recruits from large ships that required more water under the keel to anchor.[18] Appendix Table A.3 shows regressions with controls and with controls and region fixed effects. The beta coefficient of deep sea distance is bigger for large ships than for shallow ones (Appendix Table A.3) and the difference is significant in cols 1 vs 3 ($p = 0.03$). While the coefficients are smaller inthe fully saturated specifications in cols 2 and 4, and the coefficient on size remains greater for the ships with deep holds, the difference is not significant at conventional levels ($p = 0.22$). In combination, these results provide support for our identification assumptions.

Figure 6-Panel D analyzes the balancedness of our instrument. We report β-coefficients from separate regressions where we correlate demographic, economic and geographic characteristics with the distance to the deep sea. In each regression we include only coastal cells and control for the distance to the coast, asking whether distance to the deep sea has additional predictive power. Two results stand out. First, larger and more populated cells are farther from the deep sea. This result is likely a product of the way we construct our grid: cells partially covered by sea have smaller land area and are home to fewer people. They are also closer to the deep sea.[19] Density (log people per square meter of land) is not correlated with the instrument, suggesting that the 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,

[17]The depth of a ship's hold and its draught are highly correlated, but not identical. Depth of hold is available for almost all navy ships; draught for less than half.

[18]We consider ships with a deep draught those with a depth of the hold of 5m or more: they are overwhelmingly 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 only consider recruits with less than three years at sea (landsmen and ordinary seamen). This excludes officers (who joined voluntarily) and experienced sailors who are likely to have rotated in from a different ship and for whom the current vessel would not be informative of the ship which they initially joined.

[19]Cells are equally sized, so they vary in land area only because some cover the sea partially. Distance to the coast does not absorb all variation in area because almost all of this variation is from cells with the centroid on the sea and distance to the coast equal to zero.

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) because of land suitability. The other observables shown in Figure 6-Panel D are remarkably balanced with respect to the instrument, including 1801 agricultural share. While we do not observe detailed occupations and cannot test whether the instrument predicts fishermen, we note that they were unlikely to be classified together with agricultural workers, and that many of them were exempt from naval service (Dancy, 2018). 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 3 reports IV results. Panel A, cols 1–2 show the first stage: distance to the deep sea strongly predicts naval recruitment: A one s.d. increase in distance to the deep sea reduced naval recruitment by 0.13 to 0.17 s.d. The first-stage is strong, with an F-stat of 13–25, 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 many 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 $p \leq 0.002$, and 10% confidence intervals calculated with tF method of Lee et al. (2022) do not include zero, demonstrating that there is no cause for concern about weak instrument problems. First stage, reduced form and IV results are robust to methods that account for spatial correlation (Conley, 1999; Ibragimov and Müller, 2010; Conley and Kelly, 2025): results are discussed in section 5.3.

The coefficients indicate that increasing naval recruitment by 1 s.d. led to a 0.6–1.0 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 ($p \leq 0.01$). Using log machines as dependent variable confirms these conclusions (Appendix Table A.1).

In sum, naval recruitment led to labor-saving technology adoption—evidence of factor biased technical change during the Industrial Revolution. Two-stage least squares suggest the effect of labor scarcity was causal. Table A.4 analyses gender ratios with our instrument and further supports the idea that recruitment promoted adoption because it caused a shortage of men. The table shows that in the coastal

sample, greater recruitment predicts more skewed gender ratios both in the OLS and in the IV. Areas far from the deep sea were also home to significantly more men relative to the number of women.

One possible critique to the logic of our results is that Royal Navy recruitment could not possibly affect the rural labor market. In normal times, the only legal impressment was that of seamen, who would not have been employed on a farm had they not joined the Navy. We discuss in Section 1.3 how the total population of experienced seamen fell short of the need of the Royal Navy, which filled the gaps by accepting large numbers of inexperienced "landsmen," recruited largely through the same channels used for expert seamen. Appendix Table A.5 and Table A.6 provide empirical support to these claims. Appendix Table A.5 uses a subset of our recruit data to show that landsmen predict adoption both in the OLS and in the IV. Importantly, that Table also demonstrates that our instrument predicts the recruitment of this important group of workers: while the Royal Navy preferred experienced seamen, it was forced to recruit broadly, and deep sea constrained all of her recruitment. This is confirmed by Appendix Table A.6 that shows that Impress Service offices were located disproportionally closer to the deep sea, increased naval recruitment, including of landsmen and both labor saving and non-labor saving technology spread faster in their vicinity.[20] Distance to impress offices is not significantly related to army recruitment. While our measure of landsmen is very noisy, these results provide substantial support to our arguments.

Never takers. One simple way to validate our IV-exercise is to look at never-takers, in the spirit of D'Haultfœuille et al. (2021). If the exclusion restriction holds, then areas of Britain without naval recruitment should *not* show any effect of distance to the deep sea on adoption: where there are no "compliers," our instrument should have no predictive power for the adoption of labor-saving machines. Appendix Table A.7 confirms that never-taker areas—areas with one or no naval recruits—show no effect of deep sea distance on the adoption of labor-saving machines.[21] One limitation of this analysis is that, with large measurement error, it is possible that even "never taker" cells sent more than one recruit to the Navy. Thus, col 4 of the same table uses a different definition of "never taker:" the 10 percent of cells that lie furthest from one of the Impress Service *rendezvous*. The Impress Service raised a large number of recruits (Appendix Table A.6): in areas that were beyond its reach, deep sea access shows no effect on adoption.

[20]Note that the coefficient for non labor saving technology is half as large as for labor-saving, and somewhat less significant.

[21]In the 44 coastal cells with no naval recruits only one adopted labor-saving machines (2%). For this exercise we consider "never takers" to be those cells with zero or only a single naval recruit.

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.[22] There are two likely sources of bias. First, severe measurement error stems from sampling—we only have muster rolls for about 1/3 of ships, and of the individual sailor entries, only 30% contain precise information on geographical origin. Additionally, records are derived from hand-written documents kept by clerks with few incentives to give uniformly detailed, accurate information on the geographical origin of sailors. This noise alone may explain a large share of the OLS–IV difference.[23] Second, omitted variables are likely to introduce further downward bias. To see this, recall that the navy preferred to recruit sailors in trading centers: areas with a larger population, pubs, a relatively small agricultural sector, and little need for threshers and similar machines. Our IV sidesteps this issue because it identifies the effect of recruitment in areas where the navy recruited for exogenous reasons (deep sea). In sum, noise in our explanatory variable and unobservable confounders can rationalize significant downward bias in the OLS and help to explain the substantial difference between OLS and IV.

3.4 Synergies

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

3.4.1 Synergies between Labor Shortages and Mechanical Skills

The most prominent alternative to Allen (2009) hypothesis emphasizes the role of human capital (Mokyr, 2009). Workers with advanced mechanical knowledge were particularly important for developing new machines and for maintaining them. To measure the availability of mechanical knowledge necessary to support the spread of advanced technologies during the Napoleonic Wars, we assemble new, granular data from three sources: the number of young men who apprenticed to a mechanical master, the number of inventors of machines and the mentions of words signaling mechanical knowledge/use of machinery in newspapers at the time. These additional data allow us to identify an important synergy—areas of Britain where mechanical knowledge was abundant show faster adoption of labor-saving machines when labor is scarce.

[22] We find limited evidence of significant differences in compliers: Appendix Table A.8 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 be similar to the ATE of OLS.

[23] Appendix Figure A.11 plots error-in-variables OLS estimates against different levels of reliability in recruitment. Reliability lower than 30% (not implausible given the nature of the data) would explain the entire OLS–IV difference.

Figure 7 presents the basic patterns. Panel A shows that areas with lower scores for mechanical skills had markedly lower take-up of labor-saving machinery. The next two panels examine the marginal effect of total (Panel B) and Navy (Panel C) recruitment on labor-saving machine adoption in a simple OLS interaction. It shows that the higher the level of mechanical skill, the greater the effect on technology adoption. The corresponding statistical result is in Table 4-Panel A, col. 4, showing a strong and highly significant effect.

The first stage of our two endogenous variables shows strong predictive power for distance to the deep sea and the interaction of mechanical knowledge and deep sea distance (Panel B, col. 1–4). In col. 5 and 6 of Panel A, we show the instrumental variable results. Recruiting intensity is a strong predictor, but the t-statistic on the interaction in the second stage is below standard levels of significance, while the point estimate is close to OLS estimates in cols 3–4. IV-estimation with interacted variables is known to suffer from a lack of power in the first stage, as the two endogenous variables, the instrument, and the interacted instrument are highly correlated. In col. 5 and 6 in Panel B, we focus on the reduced form, which suggests that mechanical skills appear to have magnified the effect of distance to deep sea (p-value of the interaction = 0.08). Figure 7 Panel D illustrates the overall pattern: the higher mechanical skills in an area, the greater the negative effect of distance to the deep sea on machine adoption. The statistical results demonstrate that both distance to the sea and the interaction of distance with mechanical knowledge strongly and negatively predict labor saving technology use.

These results suggest that both labor scarcity and human capital availability were important factors for technology adoption both individually and in combination. In other words, it does not appear that the two main theories of the Industrial Revolution are mutually exclusive (Allen, 2009; Mokyr, 2009): they may in fact have reinforced each other.

3.4.2 Other Drivers of Growth

Additional factors such as coal, finance and slave wealth also contributed to British growth during the 19th century. We investigate synergies between military recruitment and these factors in Appendix Tables A.9, A.10, and A.11. As in Table 4 examining synergies with mechanics, we analyse the effects under OLS as well as for the reduced form, first stage, and two-stage least squares.

Overall, we find no significant, systematic effects. Heblich and Trew (2019) examine the effects of finance on development. Appendix Table A.9 shows significant interactions with recruitment under OLS, but not in the reduced form or two-stage least squares. For the first stage, we find no significant interaction effect. Ferni-

hough and O'Rourke (2021) argue that coal availability influenced the geography of economic development in England. Appendix Table A.10 shows coal availability does not interact systematically with recruitment. The coefficients under OLS have the wrong sign, and are small and insignificant in the two-stage least squares. Only one of the two reduced form specifications seem to suggest that coal deposits magnified the effect of distance to deep sea (Panel B, col 6), but the weak first stage (Panel B cols 1–4) makes us cautious to draw conclusions from this one result. Similarly, proximity to slave ports (Heblich et al., 2022) does not interact significantly with recruitment (Appendix Table A.11). OLS results are wrongly signed and insignificant, and so are the reduced form effects. 2SLS results are inconsistent and interaction effects, insignificant. Across alternative explanations, we find that our main variable—naval recruitment—is remarkably stable even after the inclusion of (and interaction with) additional factors.

3.5 Long-term Consequences

After the end of the war, labor shortages eased, but mechanization continued apace: We observe almost as many machines after 1820 (2,171) as before (2,293). Naval recruitment correlates less with later adoption but remains a significant predictor in the two-stage least squares (Appendix Table A.12), possibly because the machines allowed farmers to market the harvest quickly, avoiding to sell into lower prices: when someone adopted, everyone had to do the same to avoid being the last on the market (Hobsbawm and Rudé, 2014). Later adoption was also facilitated by productivity gains that made machines competitive at lower wages. In this section we ask: Did induced adoption in areas with labor shortages matter for the pace of subsequent technological improvements? And did adoption accelerate the move out of agriculture?

For the pace of technological progress, we focus on threshing machines because of the unique data provided by the RASE competitions. Table 5 shows that adoption and recruitment predict productivity of entrants' designs. We find that more machines in a county lead to machines that are, on average, more productive in the RASE competitions. This is suggestive of learning-by-doing effects. This pattern holds for both OLS and two-stage least squares, with larger effects from the IV estimation. We find positive association with overall and navy recruitment, though overall recruitment is not precisely estimated (col 3 and 4). When we instrument navy recruitment with distance to the deep sea (col 5), we see a large and significant effect, and distance to the deep sea directly predicts markedly lower productivity of machines entered in RASE competitions (Panel B-col 3). However, it is important to acknowledge that the long time span and relatively sparse data make it diffi-

cult to explore mechanisms in-depth. Moreover, intervening events complicate the interpretation of these estimates. Despite these caveats, these results support the idea that adoption can be instrumental for invention: 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.

Did accelerated adoption of labor-saving machinery affect structural change? Our data on machine adoption allow us to examine this question, but are observed with substantial error. In Appendix Table A.13 we regress the log of agricultural families in the 1831 census on the adoption of labor- and non-labor saving machines, as well as the stock of agricultural workers in 1801.[24] We find that labor-saving machine adoption correlates negatively with the share of agriculture (a result similar to Bustos et al., 2016). When we instrument with distance to deep sea, we obtain large, negative, significant coefficients. The reduced form similarly shows a significant relationship between agricultural shares and distance to the deep sea (controlling for distance to coast). IV and OLS estimates deviate substantially in size, probably because of measurement error. If we take the OLS coefficients at face value, a move from the 25th to the 75th percentile of machine adoption would have lowered the agricultural family share by 1.4% of the interquartile range under OLS, and by 28% of the IQR under 2SLS.[25] In contrast, non-labor saving machines are associated with a higher agricultural labor share.

In combination, our results on subsequent technology improvements and structural change are suggestive of broader long-term consequences—the extended period of high wages and labor shortages during the Napoleonic Wars may have accelerated the move out of agriculture as well as the pace of productivity improvements.

4 Alternative Explanations and Robustness

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

4.1 The Role of Commercial Ports and the Land Market

There are two potential confounders of our results: commercial shipping and the land market.[26] One alternative interpretation of our results is that military recruitment

[24]Sample size falls as we drop a few urban locations with no agricultural families in 1831. We exclude them since our focus is not on cases of complete exit where neither machines nor farm work remain.

[25]If we estimate an error-in-variable model with reliability 45%, higher than the reliability implied by the 1830 data on machinery, we obtain an estimate of 17% of the IQR.

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

had no major, differential impact on labor shortages as such. Instead, all ports in England boomed during a period of maritime warfare, siphoning off labor. To account for this, we digitize data on shipping traffic from Lloyd's List, a periodic publication tracking the arrival of large ships, both military and non-military, in British harbors (and select foreign locations).

First, we evaluate the extent to which the Royal Navy and the merchant navy used the same ports. Lloyd's List data on ship movements shows that the top seven naval ports accounted for 95% of all 1799–1800 Royal Navy vessels. Ports with more than 25% of all traffic by Royal Navy ships we catagorize as "naval". Those ports were also visited by 5,420 commercial ships, equivalent to only 29% of all commercial traffic. In contrast, the busiest ten non-military ports handled 66% of all commercial shipping, and received less than 4% of all Navy vessels. Second, the biggest commercial ships were considerably smaller than the first-rate ships-of-the-line of the Navy: for instance, when the Royal Navy purchased the largest East Indiaman, it converted it to a fourth-rate ship. The difference in size between military and commercial ships explains why the location of commercial ports was not influenced by the distance to the 12.5m bathymetric line: As cols. 4 and 8, Table A.2 show, distance to the deep sea correlates strongly with distance to military ports, but not with distance to commercial ports. In sum, navy and commercial ships had different sizes and used distinct ports: these differences explain why depth requirements differed.

We account for the presence of commercial ports in all our specifications. In addition, Appendix Table A.14 shows that including also the distance to the busiest commercial ports does not alter results, whether we consider the top 3 ports, the top 15, or anything in-between. First stage, reduced form and IV coefficient remain stable and significant.

Reverse causality is also a theoretical possibility: Naval recruitment may have created labor shortages, driving up the cost of labor and in turn, making farm sales (where machinery would then be listed), more likely. To address this potential concern, we geolocate more than 14,500 advertisements publicizing the sale or lease of a farm between 1800 and 1820.[27] This also covers farms that had no machines on their premises. The total number of farm sales is part of our baseline controls, and controls for the state of the land market at the beginning of the 19$^{\text{th}}$ century—without any effect. Additionally, in Appendix Table A.15 we estimate reduced form and IV with log total farm ads or a dummy for at least one farm ads as

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

dependent variables. Results differ starkly from machine adoption: reduced form and IV estimates have sometimes the wrong sign, are close to zero and never significant. These results suggest that reverse causation is non-existent, and that the impact of recruitment on the land market is unlikely to confound our results.

5 Robustness Checks

5.1 Extensive Margin and Discrete Choice Models

Our dependent variable, machine adoption, has many zeros and is skewed. We focus on the extensive margin—using a dummy for whether machine adoption happened at all—and estimate probit regressions (logit regressions yield similar results). Appendix Table A.16 first reports Probit results, using all recruits as the explanatory variable, with full controls, with and without region fixed effects. Recruitment predicts adoption when the technology is labor-saving but not when it is not. The table also shows similar results when the explanatory variable is naval recruitment. The IV-Probit coefficients show large and significant results for labor-saving but not for non-labor saving machinery. Finally, the table reports the reduced form, where distance to the deep sea predicts the adoption dummy with a Probit: the coefficient is negative and has p-value = 0.1. Results remain strong across specifications, and the marginal effect estimated at the mean of the recruitment distribution is close to the estimate of the linear probability model.

Second, we use discrete choice models for count variables. We choose Poisson and the control function of `ivpoisson` for the IV. Appendix Table A.17 shows results for labor-saving and non-labor-saving machines. Total recruitment and naval recruitment are strong predictors of labor-saving machine adoption in the full sample. IV Poisson estimates in the coastal sample also indicate a positive effect of naval recruitment on adoption of these machines. Finally, distance to the deep sea strongly predicts less adoption also with this model. Marginal effects (reported at the bottom of the estimates) are near-identical to OLS.

Third, we use zero-inflated Poisson regressions, in which we first use no farm ads and distance to the closest newspaper above 35 km to predict whether a cell has no machines and then fit the Poisson model on the rest of the distribution. Appendix Table A.18 reports the impact on adoption of total recruits, Navy recruits and distance to deep sea. Conclusions are unaffected.

5.2 Matching Exercises

Matching methods offer an alternative way to identify causal effects. Appendix Figure A.12 presents results from CEM, entropy balancing and Appendix Table A.19

estimates with nearest neighbor matching. We define "treated" units as those with recruitment above the sample median—these areas had significantly more machines. 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 the effect of recruitment on adoption is unaffected. R^2 are 3-4 times larger, but effects remain strong. Appendix Figure A.12 also reports in blue entropy balancing estimates (Hainmueller, 2012). This method keeps the full sample but re-weights observations to ensure balance across treated and controls. This leads to larger effects of recruitment on adoption. Finally, Appendix Table A.19 shows nearest neighbor matching estimates, where we restrict the sample to observations that are close in terms of geography, population, agricultural share, wheat suitability and access to finance (country banks) and new technology (patents, steam engines, apprentices). We match each high-recruitment cell to one, three and five similar cells with low recruitment overall or in the same region. Estimates are significant and close to baseline results.

5.3 Spatial Inference

Spatial correlation can lead to understated standard errors. Labor-saving machines do not appear to have a spatial unit root: when we implement the tests of Müller and Watson (2024) with Becker et al. (2025) Stata command we cannot reject the null that the variable is I(0) (p-value = 0.346 and 0.341 in the full and coastal sample, respectively) and we reject the null that it is I(1) (p-value = 0.049 and 0.030). Nevertheless Figure 1-Panels C–D display spatial dependence in our dependent variables, and Appendix Table A.20 displays Moran's I p-values, which suggests spatial correlation disappears beyond 600 km in all specifications with region fixed effects, though it persists in the OLS without these fixed effects. Data prevents us from estimating Moran's I at larger thresholds. We show the robustness of inference to spatial correlation in four ways. First, we correct parametrically standard errors with the Conley (1999) formula. Appendix Table A.21 shows corrections when spatial correlation is assumed to disappear after 50, 100, 200, 400, 600, 800 and 1,000 km, as well as county-level clustering. Standard errors initially rise, yet results remain strong in all specifications; assuming spatial dependency over longer distances increases significance. Second, we apply the method by Ibragimov and Müller (2010), and partition our data into four samples, based on the map of English labor markets in Caird (1852). We then estimate separate coefficients in these four samples and calculate the significance of the average coefficient with an exact t-test. Because the four samples lie far apart, the four estimates are likely uncorrelated and the t-test has good statistical properties (Ibragimov and Müller, 2010). Appendix Table A.22

shows the results: reduced form and IV have p-values of 0.009 and 0.024, while OLS has p-value of 0.066-0.073 and the first stage of 0.090. Third, in Appendix Table A.23 we show results are unaffected when we control linearly for coordinates. Fourth, we follow Conley and Kelly (2025) and include in all regressions a B-spline in latitude and longitude. We use the Bayesian Information Criterion (BIC) to select among all possible principal components of splines of base 3 through 6: Appendix Table A.13 shows the BIC for the main models. We then re-estimate all models after including the spline with the lowest BIC: Appendix Table A.24 reports estimates along with p-values calculated with standard errors heteroschedastic-robust, clustered at county level or calculated with Conley (1999) formula and a linear decay at 200 km. Appendix Table A.25 reports t-stat inference of Ibragimov and Müller (2010) to regressions augmented with these B-splines. Results remain remarkably significant through these very demanding specifications.

Taken together, these exercises show that our results are not impacted by correcting for spatial autocorrelation.

5.4 Plausibly Exogenous

Are IV estimates robust to small violations of the exclusion restriction? Distance to deep sea is uncorrelated with pre-war characteristics and doesn't predict maritime trade, army recruitment nor farm ads, broadly supporting the exclusion restriction. In this section we also present the results of the test of Conley et al. (2012), which identifies confidence bounds of the IV estimates when the exclusion restriction is violated. Appendix Figure A.14 reports these bounds on the y-axis, against the assumed violation on the x-axis (i.e. the assumed direct effect of distance to the deep sea on adoption). Panel A shows the specification with all controls and Panel B adds region fixed effects. We indicate the reduced form coefficient as a vertical line for reference. In both specifications, the direct effect must account for more than half of the reduced form coefficient for the IV to become insignificant. Such large direct effects of deep sea on adoption appear unlikely.

5.5 Alternative Samples, Controls, Recruitment Definition, and Machine Classification

Results are robust in several alternative samples, controls and specifications. First, our main analysis in Table 2 excludes urban areas—where farm implements are unlikely to be used—but it includes all cells within 50 km from a newspaper, regardless of whether they had farms for sale or lease. None of these choices is crucial. Including urban cells does not affect our results (Appendix Table A.26), nor does excluding cells never mentioned in farm ads (Appendix Table A.27) or including those that lie

farther from 50km from a newspaper (Appendix Table A.28).

Second, locations close to ports (naval or commercial), supply yards and those in Wales may bias results in our favor. Several confounders are possible: wartime activity close to Navy ports may affect labor markets directly. Nineteen victualling yards supplied the British armed forces with food and other provisions. High demand for foodstuffs there may have promoted technological progress, confounding our estimates. Commercial ports may expand during the war, leading to tighter labor markets. 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 these areas may bias results in our favor, but in practice none of them drives our conclusions: our results are robust under different sample restrictions, some very conservative. Appendix Table A.29 drops cells within 8 km from a Naval port; Appendix Table A.30 drops 59 cells within 8 km from one of the victualling centers, and Appendix Table A.31 drops both. Appendix Table A.32 drops all cells within 8 km from either a commercial or a Navy port. This is particularly demanding for the reduced form and IV regression, where the restriction halves the sample size. Results are robust across specifications: OLS results remain strong, as do reduced form results. The two-stage least squares estimate on this sample, with half the observations and all controls and fixed effects, has a point estimate larger than the baseline but with half the baseline sample size it is imprecisely estimated (p-value = 0.2). Port activity is not confounding our results. Also Wales does not drive our conclusions: excluding it leaves our results unchanged (Appendix Table A.33).

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

Fourth, we consider three additional potential confounders: Parliamentary enclosures, wheat prices and the fact that some cells are so close to the sea that their centroid lies offshore. None affects our conclusions. Appendix Table A.34 controls for the share of land enclosed at the beginning of the wars (1792) as well as for the share of land enclosed during the wars (1793–1815). Data on enclosure does not cover the entire country, which reduces sample size somewhat. Enclosures enacted during the conflict promoted machine adoption, while pre-war enclosure have a zero or negative effect. Importantly, all our results are unaffected: recruitment remains a positive and large determinant of adoption both in the OLS and in the two-stage

least squares. Appendix Table A.35 allows the counties experiencing faster wheat price inflation to adopt at a differential rate: we find that high food inflation significantly slows adoption, but has no effect on the strength of factor biased technical change. Finally, to account for the fact that distance to sea is truncated at zero for cells with centroid in the sea, we replicate all our results including an indicator for these cells. Appendix Table A.36 shows that all results are robust.

Fifth, our labor-saving machinery classification may introduce errors. We re-estimate with threshers only (Appendix Table A.37) since they are unlikely to be assigned to the wrong category, and because they clearly saved labor—and represent the kind of expensive capital item most likely to be listed in a sales ad. Results are near-identical, confirming a significant impact of war-induced labor shortages on thresher adoption, the most important rural technology of the time.

Finally, we experiment with variations in our measure of military recruitment. We start in Appendix Table A.38 where we re-scale recruitment by 1801 male population.[28] Results remain significant in OLS and IV models. We also consider different transformations of recruitment per capita. The distribution of this variable has a high skew (44.8) and a large proportion of zeros (45%). In our baseline results we follow Chen and Roth (2023), take the natural logarithm and model the extensive margin explicitly, assigning -2 to cells with zero recruitment. This ensures cells with no recruitment receive the lowest value. Moreover, when recruitment is the dependent variable, as in the first stage regressions, it implies that the extensive margin is valued at 200 log points. This choice is arbitrary but inconsequential: Appendix Tables A.39 and A.40 show that all results survive when we assign -1 or -3 to cells with no recruitment.

6 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, Britain fought on average in one year out of three (Brewer, 1988). Britain was also home to a large number of scientists and "tinkerers"—men from all walks of life interested in improving technology (Mokyr, 2009).

In this paper, we argue that these three important features are closely connected, and facilitated the transformation of the First Industrial Country: Wartime labor shortages boosted technology adoption in industrializing Britain. Greater use of

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

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 one of the largest navies in history, as well as a sizable army. Sailors and soldiers were not available to work in the fields and factories. In places with heavy recruitment, the adoption of a critical labor-saving technology—threshing—and other labor-saving machines took off. The same is not true of non-labor saving machines.

After the end of the wars, when men returned from war, the new machinery remained in place. Efficiency (and reliability) improvements were one reason. Data from agricultural competitions show that in places where more machines had been adopted due to naval recruitment 1793–1815, the scale of 'tinkering' and the pace of progress was faster, and so was structural change. As Allen (2009) argued, adopting new technologies responded to factor scarcity. However, the artisans and experimenters highlighted by Kelly et al. (2022) also contributed to faster technological progress. Our results suggest a unified interpretation, documenting a potentially important synergy between exogenously-induced labor scarcity and mechanical skills; where a confluence of both occurred, technology advanced faster. This apparent synergy lends empirical support to general theories of directed technological change (Hémous and Olsen, 2022); it suggests the potential for automation to drive up the demand for complementary, 'reinstating' skills (Acemoglu and Restrepo, 2018).

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Tables

Table 1: The impact of recruitment on the labor market: gender imbalances and wages

	(1)	(2)	(3)	(4)	(5)	(6)
	log gender ratio		Wartime wages		Pre-war wages	
Panel A.	1801-11		1792–1811		Pre-1792	
log total recruits per capita	0.115***	0.130***	0.193***	0.147**	-0.109*	-0.109*
	[0.000]	[0.000]	[0.004]	[0.022]	[0.096]	[0.079]
R^2	0.172	0.201	0.227	0.282	0.345	0.388

	log gender ratio		Wartime wages		Pre-war wages	
Panel B.	1801-11		1792–1811		Pre-1792	
log Royal Navy recruits per capita	0.145***	0.150***	0.148**	0.112*	-0.143**	-0.154***
	[0.000]	[0.000]	[0.037]	[0.092]	[0.018]	[0.008]
R^2	0.179	0.205	0.215	0.276	0.351	0.396
Mean dep. var.	0.036	0.036	1.787	1.787	1.358	1.358
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
Wheat price & season FEs (2)	No	No	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	Yes	Yes
Observations (grid cells)	2596	2596	469	469	350	350

Notes: OLS estimates of Equation (1) with gender ratios and wages as dependent variables. Panel A: main explanatory variable is log total recruits per capita. Panel B: main explanatory variable is log Royal Navy recruits per capita. Dependent variables are: cols. 1–2 log 1801–11 gender ratios; cols 3–4 agricultural wages in winter and summer during the war years of 1793–1811; cols 5–6 agricultural wages in winter and summer before 1793. Units of observation are equally sized hexagonal cells. Full controls include: log 1801 population, log area, wheat suitability, agricultural and trade employment shares, log farm ads, country banks, log distance to post-towns, log distance to newspapers, a dummy for having a commercial port within 8 km, dummies for steam engines, patents, apprentices, ruggedness and bounty of the sea. Cols 3–6 also include season fixed effects. We report beta coefficients and p-values calculated with robust standard errors in parentheses below ***p<0.01, **p<0.05, *p<0.1.

Table 2: OLS evidence: Labor-saving and non-labor saving machine adoption

	Dep. var.: Labor saving machines in grid cell					
Panel A.	(1)	(2)	(3)	(4)	(5)	(6)
log total recruits per capita	0.185***	0.078***	0.083***	0.077***		
	[0.000]	[0.000]	[0.000]	[0.000]		
log Royal Navy recruits per capita					0.067***	
					[0.003]	
log British Army recruits per capita						0.083***
						[0.000]
R^2	0.034	0.200	0.209	0.222	0.221	0.223
Mean labor saving machines	0.769	0.769	0.769	0.769	0.769	0.769

	Dep var.: Non labor saving machines in grid cell					
Panel B.	(1)	(2)	(3)	(4)	(5)	(6)
log total recruits per capita	0.086***	0.024	0.026	0.024		
	[0.000]	[0.258]	[0.223]	[0.262]		
log Royal Navy recruits per capita					0.004	
					[0.863]	
log British Army recruits per capita						0.043*
						[0.082]
R^2	0.007	0.057	0.067	0.071	0.070	0.072
Mean non labor saving machines	0.141	0.141	0.141	0.141	0.141	0.141
p-value labor saving = nonÂ laborÂ saving	0.000	0.000	0.000	0.001	0.001	0.002
Demography, area, soil and farm ads	No	Yes	Yes	Yes	Yes	Yes
Technology, skills, finance and geography	No	No	Yes	Yes	Yes	Yes
Region FEs (5)	No	No	No	Yes	Yes	Yes
Observations (grid cells)	2603	2603	2603	2603	2603	2603

Notes: OLS estimates of Equation (1). Panel A: dependent variable is labor saving machines in 1790–1820. Panel B: dependent variable is non-labor saving machines in 1790–1820. Units of observation are 2603 equally sized hexagonal cells. Demography, area, soil and farm ads controls are: log 1801 population, log area, wheat suitability, agricultural and trade employment shares, and log farm ads. Technology, skills, finance and geography controls are: country banks, log distance to post-towns, log distance to newspapers, , a dummy for having a commercial port within 8 km, dummies for steam engines, patents, apprentices, ruggedness and bounty of the sea. The p-value at the bottom of the table tests the null that the coefficients in Panels A and B are the same. We report beta coefficients and p-values calculated with robust standard errors in parentheses below. ***p<0.01, **p<0.05, *p<0.1.

Table 3: First stage, reduced form, and two-stage least squares (coastal sample)

	(1)	(2)	(3)	(4)
	Dep. var.: log recruits per capita			
Panel A. First stage and placebo	Royal Navy		British Army (placebo)	
Distance to deep sea	-0.165***	-0.125***	0.047	-0.001
	[0.000]	[0.000]	[0.214]	[0.975]
R^2	0.244	0.276	0.119	0.129
Mean log recruits per capita	-0.275	-0.275	-0.941	-0.941
Kleibergen-Paap F-stat first stage	25.4	12.7	1.5	0.0
p-value Navy = Army			0.000	0.000
	Dep. var.: Machines			
Panel B. Reduced form	Labor saving		Non labor saving	
Distance to deep sea	-0.094***	-0.128***	-0.006	-0.043
	[0.001]	[0.000]	[0.839]	[0.206]
R^2	0.206	0.218	0.062	0.071
p-value labor saving = non labor saving			0.001	0.000
	Dep. var.: Machines			
Panel C. Two-stage least squares	Labor saving		Non labor saving	
log Royal Navy recruits per capita	0.567***	1.023***	0.038	0.344
	[0.006]	[0.005]	[0.838]	[0.213]
tF inference: 5% confidence interval	[0.07, 1.14]	[-0.09, 2.29]	[-0.15, 0.18]	[-0.18, 0.43]
tF inference: 10% confidence interval	[0.23, 0.99]	[0.32, 1.88]	[-0.10, 0.13]	[-0.07, 0.32]
Anderson-Rubin test (p-value)	0.001	0.000	0.839	0.206
p-value labor saving = non labor saving			0.006	0.005
Mean machines	0.798	0.798	0.121	0.121
Distance to coast	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes
Observations (grid cells)	887	887	887	887

Notes: Identification of the effect of recruitment on machine adoption. Sample consists of 887 cells within 15 km from the coast. Dependent variable: Panel A: log Navy recruits per capita (cols 1–2) and log Army recruits per capita (cols 3–4). Panels B and C: labor-saving machines (cols 1–2) and non-labor saving machines (cols 3–4). Full controls include: distance to the coast, log 1801 population, log area, wheat suitability, agricultural and trade employment shares, log farm ads, country banks, log distance to post-towns, log distance to newspapers, a dummy for having a commercial port within 8 km, dummies for steam engines, patents, apprentices, ruggedness and bounty of the sea. tF inference confidence intervals for IV estimates are calculated with Lee et al. (2022) method. The p-values at the bottom of Panel A test the null that distance to deep sea has the same effect on Royal Navy and British Army recruitment (col 1 vs 3 and 2 vs 4). The p-values at the bottom of Panel B and C test the null that the reduced form and IV coefficients of labor-saving and non-labor saving machines are the same (cols 1 vs 3 and 2 vs 4). We report beta coefficients and p-values calculated with robust standard errors in parentheses below. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Adoption: Synergies between mechanics and labor scarcity

	(1)	(2)	(3)	(4)	(5)	(6)
	Dep. var.: Labor saving machines in grid cell					
Panel A. Adoption and recruits. Recruits are:	total recruits		Navy recruits		Navy recruits	
log recruits per capita	0.083***	0.076***	0.056**	0.068**	0.600***	1.050***
	[0.000]	[0.000]	[0.049]	[0.026]	[0.003]	[0.003]
log recruits per capita × mechanics (PCA)	0.104***	0.106***	0.137**	0.146**	0.141	0.070
	[0.003]	[0.002]	[0.043]	[0.031]	[0.304]	[0.615]
Mechanics (PCA)	0.016	0.015	0.061	0.047	0.015	-0.007
	[0.587]	[0.584]	[0.168]	[0.284]	[0.873]	[0.934]
Estimation method	OLS	OLS	OLS	OLS	2SLS	2SLS
R^2	0.223	0.236	0.225	0.235		
Mean dep. var.	0.769	0.769	0.798	0.798	0.798	0.798
Kleibergen-Paap F-stat first stage					12.8	6.9
Anderson-Rubin test (p-value)					0.002	0.000
Distance to coast	No	No	No	No	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes
Observations (grid cells)	2603	2603	887	887	887	887

	Navy recruits		Recruits × mech.		Labor saving machines	
Panel B. First stage and reduced form.	First Stage				Reduced form	
Distance to deep sea	-0.178***	-0.138***	-0.060	-0.030	-0.115***	-0.147***
	[0.000]	[0.000]	[0.232]	[0.550]	[0.000]	[0.000]
Dist to deep sea x mechanics (PCA)	-0.081*	-0.087**	-0.618**	-0.620***	-0.136*	-0.135*
	[0.061]	[0.032]	[0.010]	[0.009]	[0.073]	[0.076]
Mechanics (PCA)	0.156***	0.176***	1.084***	1.090***	0.262**	0.254*
	[0.003]	[0.000]	[0.000]	[0.000]	[0.048]	[0.061]
R^2	0.252	0.287	0.426	0.432	0.230	0.240
Mean dep. var.	-0.275	-0.275	0.362	0.362	0.798	0.798
F-stat H0: distance to deep sea = 0	28.1	14.8	1.4	0.4		
F-stat H0: distance to deep sea × mechanics = 0	3.5	4.6	6.6	6.8		
F-stat H0: both instruments = 0	14.4	8.7	7.8	9.7		
Distance to coast	Yes	Yes	Yes	Yes	Yes	Yes
Full controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FEs (5)	No	Yes	No	Yes	No	Yes
Observations (grid cells)	887	887	887	887	887	887

Notes: Heterogeneity in the effect of labor scarcity on machine adoption by presence of mechanics. Panel A: Dependent variable is labor-saving machines. Panel B: Dependent variables are log Royal Navy recruits per capita (cols 1–2); log Royal Navy recruits per capita × PCA of mechanics (cols 3–4); labor-saving machines (cols 5–6). Panel A: estimation method is OLS (cols 1–4) and two-stages least squares, with recruits and recruits × mechanics instrumented with distance to deep sea and distance to deep sea interacted with mechanics (cols 5–6). Panel B: first stages in cols 1–4; reduced form in cols 5–6. The Kleibergen-Paap F-stat in Panel A tests the null that the two instruments do not predict jointly the two endogenous variables. The F-stats in panel B test the null that the instruments do not predict the endogenous variables in separate regressions. Full controls include: log 1801 population, log area, wheat suitability, agricultural and trade employment shares, log farm ads, country banks, log distance to post-towns, log distance to newspapers, a dummy for having a commercial port within 8 km, dummies for steam engines, patents, apprentices, ruggedness and bounty of the sea. Cols 2 and 4 in both panels add five region fixed effects. Two-stage least squares (Panel A, cols 5–6), first stage and reduced form (Panel B) also control for distance to the coast. We report beta coefficients and p-values calculated with robust standard errors in parentheses below. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Productivity of Thresher Designs and Its Determinants

	(1)	(2)	(3)	(4)	(5)
	Dep. var.: Steam-thresher productivity				
Panel A. Early adoption and productivity. Estimation	OLS	2SLS	OLS	OLS	2SLS
Threshers within 50 km, 1800-20	0.206**	0.555**			
	[0.028]	[0.028]			
log total recruits per capita			0.079		
			[0.178]		
log Royal Navy recruits per capita				0.087*	0.257**
				[0.092]	[0.024]
R^2	0.522		0.520	0.520	
Mean dep. var.	2.658	2.658	2.658	2.658	2.658
Anderson-Rubin test (p-value)		0.016			0.016
Distance to coast	No	Yes	No	No	Yes
Full controls	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations (steam threshers)	306	306	306	306	306

	(1)	(2)	(3)
	Threshers	Navy Recruits	Productivity
Panel B. First stage and reduced form.	First Stage		Reduced form
Distance to deep sea	-0.937***	-2.021***	-0.520**
	[0.002]	[0.000]	[0.016]
R^2	0.962	0.896	0.523
Mean dep. var.	70.330	0.735	2.658
Kleibergen-Paap F-stat first stage	10.7	17.4	
Distance to coast	Yes	Yes	Yes
Full controls	Yes	Yes	Yes
Year FEs (5)	Yes	Yes	Yes
Observations (steam thresher locations)	306	306	306

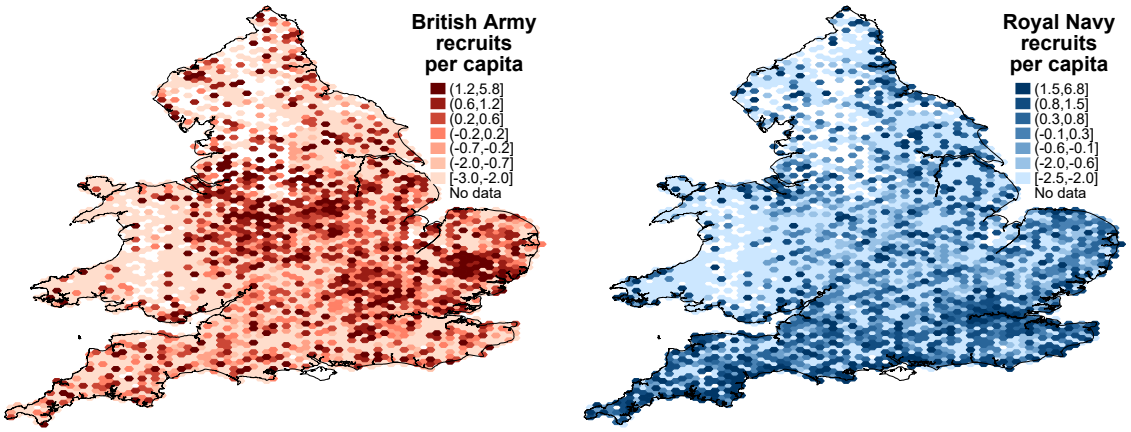
Notes: Early adoption and productivity of threshers. Panel A: military-induced early adoption and productivity of steam threshers in 1800 RASE competitions. Dependent variable: productivity of steam-powered threshers (sheaves per worker per minute). Cols 1, 3 and 4: OLS estimates. Cols 2 and 5: two-stage least squares where threshers (col 2) and Royal Navy recruitmen (col 5) is instrumented with distance to the deep sea. Panel B: first stages (col 1 and 2) and reduced form (col 3). Dependent variables are: threshers within 50 km in 1800–20 (col 1); log Royal Navy recruits per capita within 50km (col 2) and steam thresher productivity (col 3). Full controls include: log 1801 population, log area, wheat suitability, agricultural and trade employment shares, log farm ads, country banks, log distance to post-towns, log distance to newspapers, a dummy for having a commercial port within 8 km, dummies for steam engines, patents, and apprentices, ruggedness and bounty of the sea. Two-stage least squares (Panel A, cols 2 and 5), first stage and reduced form (Panel B) also control for distance to the coast. Sample consists of 306 steam-powered threshers in RASE competitions. We report beta coefficients and p-values calculated with standard errors clustered at town level in parentheses below. *** p<0.01, ** p<0.05, * p<0.1.

Figures

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

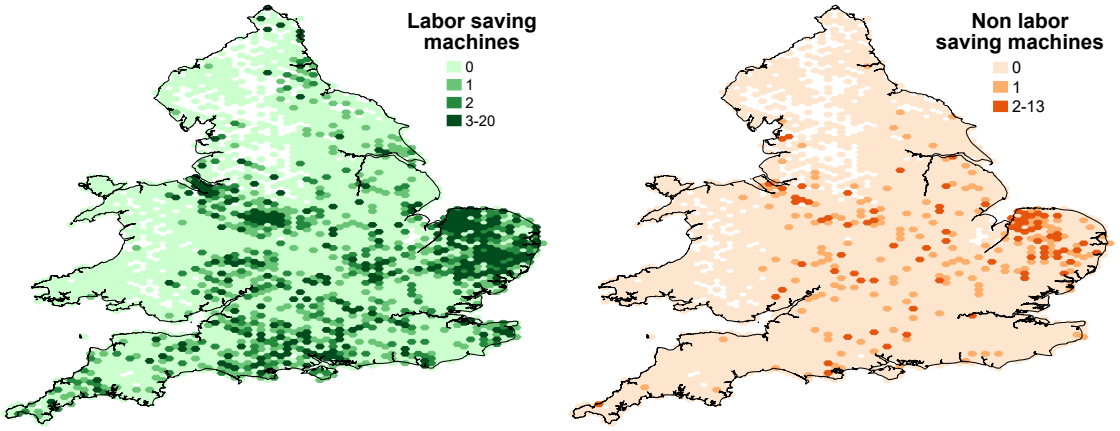
A. British Army recruits per capita

B. Royal Navy recruits per capita



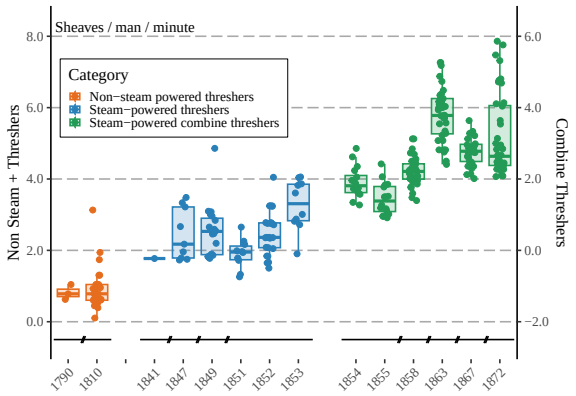
C. Locations of labor saving machines

D. Locations of non labor saving machines



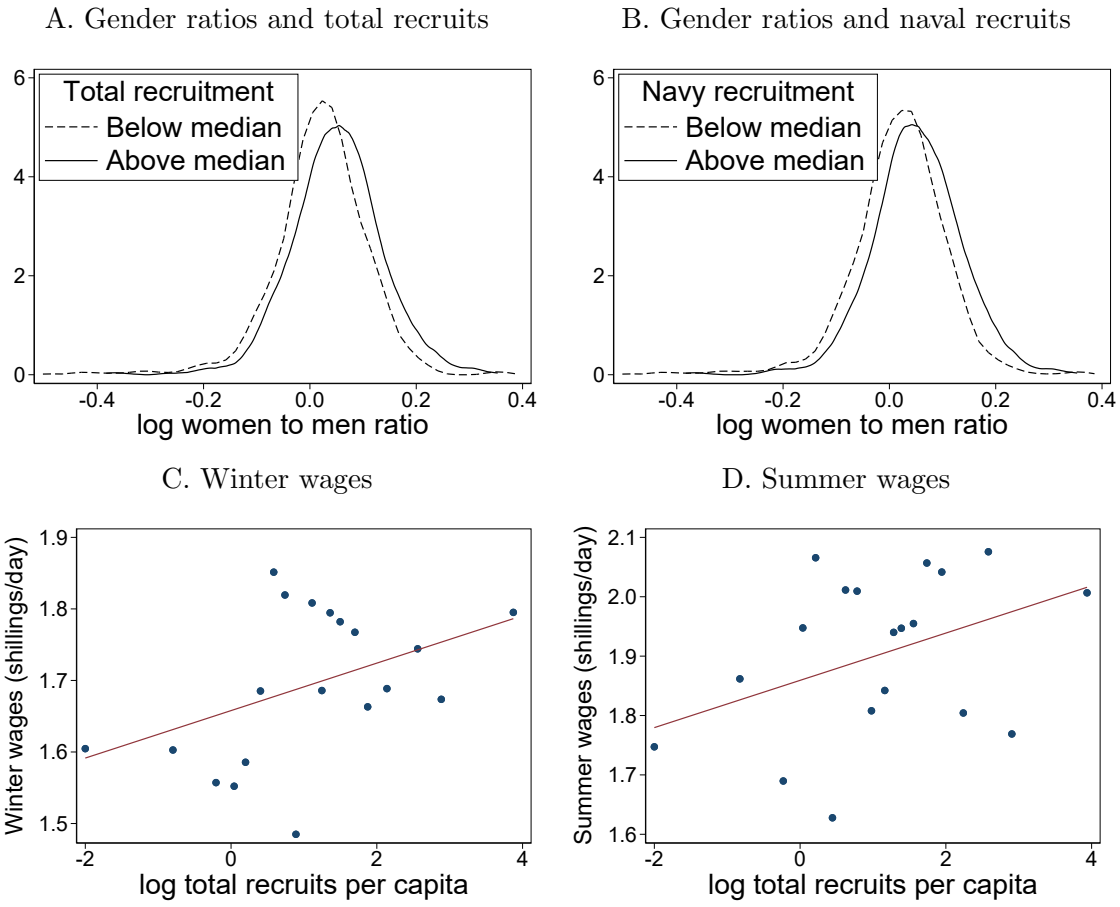
Notes: Panel A: log British army recruits 1790–1819 per 1801 capita. Panel B: log Royal Navy recruits in 1792-1815 per 1801 population. Panel C: location of labor saving agricultural machines in 1790–1820. Panel D: location of non labor saving agricultural machines in 1790–1820. Sources: Navy: Trafalgar project, Dancy (2018) and Muster rolls; Machine adoption: British Library and Findmypast (2022) and *General Views of Agriculture*.

Figure 2: Productivity of threshing machines: 1790–1872



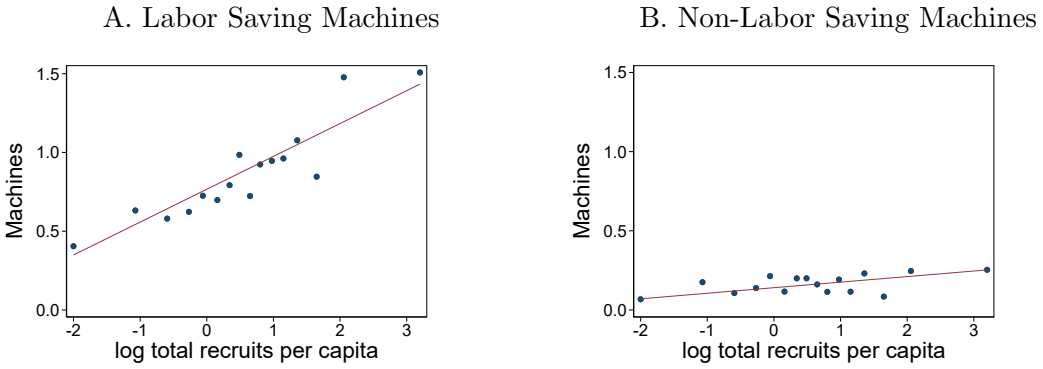
Notes: Productivity of threshing machines in sheaves of wheat threshed per full time equivalent worker in one minute. One sheaf of wheat weighs roughly 1.5kg. **Sources**: 1790s and 1810s: *General Views of Agriculture*; 1841-1872: Royal Agricultural Society of England competitions.

Figure 3: The impact of naval recruitment on the labor market



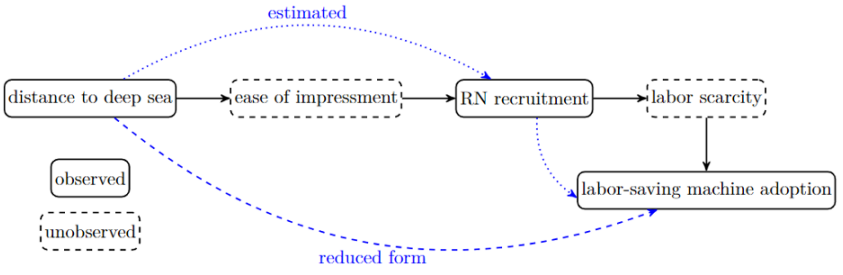
Notes: Panels A–B: Kernel density of log of the average women to men ratios in 1801–11 by intensity of recruitment. Gender ratios averaged for 1801 and 1811. Panel A: total recruitment. Panel B: naval recruitment. Panel C–D: binscatters of agricultural wages against log total recruitment per capita. Panel C: agricultural wages paid in winter (N=247). Panel D: agricultural wages paid in summer (N=223).

Figure 4: Military recruitment and machine adoption



Notes: Military recruitment and machine adoption. Unconditional binscatters with average number of agricultural machines (y-axis) against bins of log total recruitment (x-axes). Panel A: labor-saving agricultural machines. Panel B: non-labor saving agricultural machines.

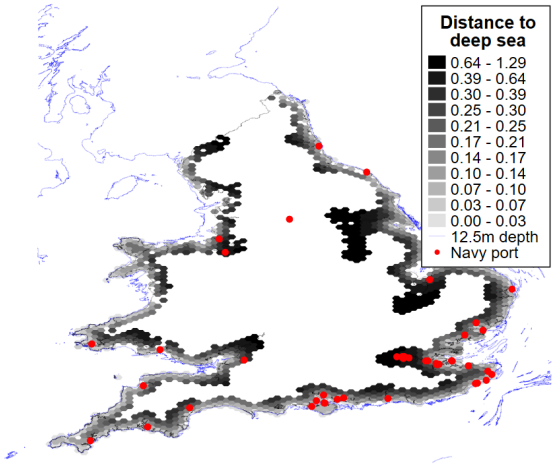
Figure 5: IV Strategy



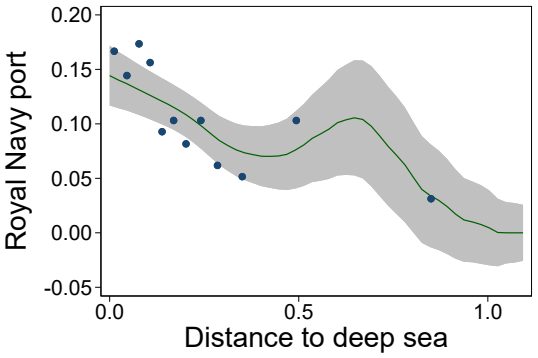
Notes: The figure summarizes the IV-strategy. Solid black arrows indicate hypothesized causal links. Dashed blue lines indicate reduced form relationships; dotted blue lines, estimated ones.

Figure 6: IV strategy

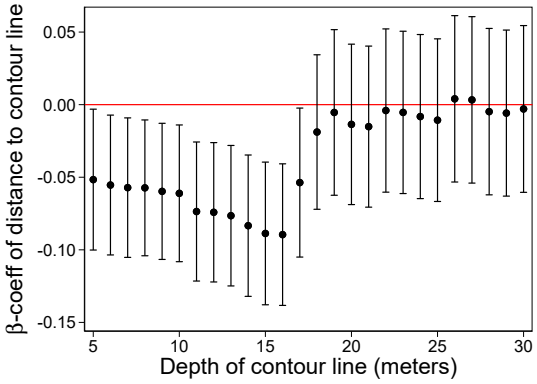
A. Deep sea and port location



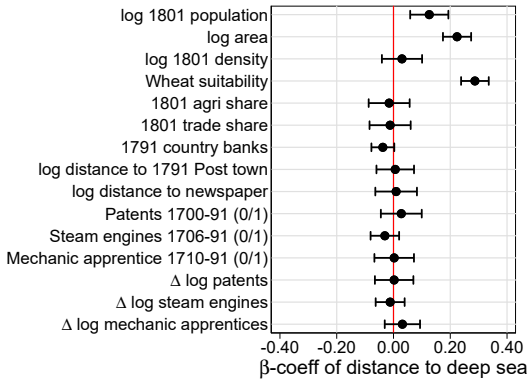
B. Navy presence and distance to deep sea



C. Distance to deep sea and Navy presence

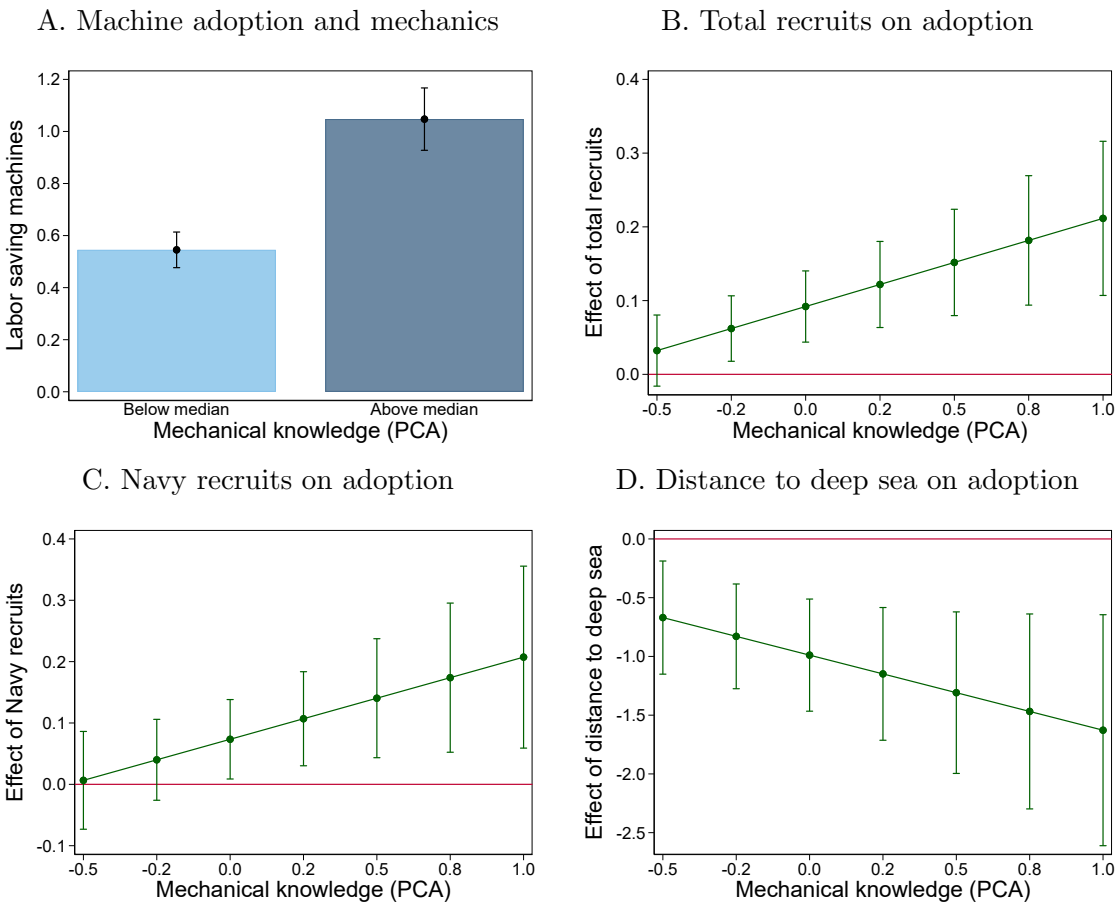


D. Balance of the instrument



Notes: Panel A: distance to the closest sea point 12.5m deep; in red Royal Navy ports. Panel B: unconditional relationship between distance to the deep sea (x-axis) and Royal Navy port presence (y-axis). Kernel-weighted local polynomial smoothing lines and 95% CI. Panel C: coefficients of distances to closest sea points of depths ranging from 5m to 30m. Dependent variable is Royal Navy port; we run 26 separate regressions, using distance to each depth between -5m and -30m; we then report each of the 26 coefficients. All regressions control for distance to coast, the full set of controls and region fixed effects, robust se for 95% CI. Panel D: coefficients of separate regressions of listed variables on distance to deep sea. We control for distance to coast in each regression; robust se for 95% CI. Sample =887 cells within 15 km of the coast.

Figure 7: Technology adoption and mechanics



Notes: Panel A: machine adoption above and below median mechanics (PCA): average and 95% confidence intervals. Panel B: marginal effect and 95% confidence intervals of the effect on adoption of log total recruits per capita as a function of mechanics. Panel C: marginal effect and 95% confidence intervals of the effect on adoption of log Royal Navy recruits per capita as a function of mechanics. Panel D: marginal effect and 95% confidence intervals of the effect on adoption of distance to the deep sea as a function of mechanics. Panels A–B: sample = 2,603 equally-sized cells. Panels C–D: sample = 887 equally-sized cells within 15 km from the coast.