RAGE AGAINST THE MACHINES: LABOR-SAVING TECHNOLOGY AND UNREST IN ENGLAND, 1830-32*

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Abstract: Can the adoption of labor-saving technology lead to social instability and unrest? We examine the canonical case of the so-called 'Captain Swing' riots in 1830s Britain. Variously attributed to the adverse consequences of weather shocks, the shortcomings of the Poor Law, or the after-effects of enclosure, we emphasize the importance of a new technology – the threshing machine. Invented in the 1780s, it spread during and after the Napoleonic Wars. Using farm advertisements from newspapers published in 60 English and Welsh towns, we compile a new measure of the technology's diffusion. Parishes with evidence of threshing machine adoption had much higher riot probabilities in 1830. Threshing machines were much cheaper to operate with water power, and they were initially only useful for wheat. We show that British parishes with streams and high wheat suitability were significantly more likely to adopt the new technology. Instrumental variable estimates suggest that the spread of threshing machines was responsible for unrest. We provide suggestive evidence that the new technology created *technological unemployment*, impoverished rural workers and led to unrest. We also show that areas with more generous poor law provision saw less rioting, even in areas where threshing machines were common: this suggests that redistribution through welfare support can facilitate technology adoption. Finally, we document that over the 20 years following the riots, adoption of labor saving technology slowed down in areas closer to the 1830-32 uprising.

Keywords: Labor-saving technology; social instability; riots; welfare support; agricultural technology; factor prices and technological change.

JEL Classification: P16, J21, J43, N33

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Technological progress has not been kind with human jobs. Since the start of the Industrial Revolution, new machines have repeatedly replaced workers and made age-old occupations outdated. Two hundred years ago, spinners and weavers lost their jobs to steam-power textile mills; more recently, computers have replaced phone operators, bookkeepers and other workers performing routine jobs (Autor, Levy, and Murnane, 2003). This in turn has put downward pressure on low-skilled workers (Acemoglu and Autor 2011), and drove up the demand for highly-skilled workers capable of operating the new equipment (Autor, Katz and Krueger 1998; Acemoglu and Restrepo 2016).

While there is ample evidence that labor-saving technological change can adversely affect workers, its social and political consequences have received less attention. Marx expected that technological change would depress the wages of the working class to such an extent that workers would eventually revolt, overthrowing the established political order. More recently, a growing literature has investigated the economic determinants of conflicts, often using exogenous shocks to commodity prices or to rainfall to identify causal effects. In this paper, we combine the perspectives of these two literatures and examine whether the introduction of labor-replacing technology can lead to social instability and political unrest. We also analyze the mechanisms that lead to unrest, and examine the consequences of technology-related unrest on subsequent innovative activity.

We investigate these questions by focusing on one famous historical episode – the “Captain Swing” riots in 1830 England. *Swing* constitutes the largest episode of political unrest in English history, with more than 3,000 cases of arson, looting, attacks on authorities, and machine-breaking across 45 counties. It ended with military intervention and severe repression, but the riots had also lasting consequences, as they ushered in a period of important political and institutional reform (Aidt and Franck 2015).

The ‘Captain Swing’ riots have been attributed to several causes (Hobsbawn and Rudé, 2014; Griffin, 2012). Most prominently among them are the Poor Laws (an early form of welfare payments), failed harvests, technological change, and the release of a large number of soldiers and mariners from military service after the end of the Napoleonic Wars. While all of these may have contributed to the outbreak of unrest, recent scholarship has cast severe doubts on the role of machinery replacing laborers as cause of unrest (Mokyr, Vickers and Ziebarth, 2015).

Using newly-collected historical data on the diffusion of threshing machines, we show that labor-saving technology was a key factor behind the riots. First, we analyze advertisements for farms on lease or sale, collected from dozens of English local newspapers, and examine whether they list mechanical threshers as part of the farm inventory. We then correlate this data with the geographical pattern of unrest. Figure 1 shows the main result: In parishes without any evidence of technology adoption (i.e. no ads for a farm with a threshing machine), the riot probability was 13.6%; in places where the new technology had been adopted, it was 26.1% -- twice as high. Using newly digitized data from the Poor Law returns, we also show that unemployment was systematically higher in parishes where threshing machines had spread. Machine-breaking in response to technological unemployment was a key part of the riots, but it also spilled over into other forms of unrest, such as arson, blackmail, and attacks on Poor Law administrators.

The link is arguably causal. Threshing machines were cheaper to operate where water power was available and adoption of the new machines was higher in areas more suitable to the use of water power because of terrain characteristics. In addition, threshing machines were initially useful only process wheat, and we find that FAO data on soil suitability to wheat cultivation strongly predicts the adoption of these machines. Crucially, we find that the combination of these two geographical characteristics – the presence of a stream that can drive a water mill and wheat suitability – is a strong predictor of both machine adoption and riots, even after controlling for these characteristics separately. This suggests that the effects of labor-saving technology on unrest are causal.

Finally, we examine some mechanisms behind our results. We find that the presence of a city with a large manufacturing sector dampens the link between machines and riots. In contrast, the enclosure movement – a process that transferred common lands to wealthy landlords – exacerbated the effect of machines on riots. Finally, we present suggestive evidence that a system of poor relief known as the Poor Laws helped workers displaced by the machines to cope with the technological shock and dampened the effect of the new technology on riots. We also present data on machine adoption and patents *after* the riots that suggest that the protest may have discouraged innovation in the two decades following the outbreak.

We contribute to two main literatures – one on labor markets effects of new technology, the other on the economic determinants of conflict. A growing literature in labor-economics has demonstrated that the IT revolution has disadvantaged less educated workers (Acemoglu, 1998; Autor, Katz and Krueger, 1998), and replaced workers performing tasks that are easy to codify (Autor, Levy and Murnane, 2003).[1] There is also good evidence that new agricultural technologies can drive workers out of agriculture (Bustos, Caprettini and Ponticelli, 2016). However, what is unclear is whether such labor-saving technological change can create political instability and social unrest.

Most of the theoretical contributions on the determinants of political instability and social unrest begins with the observation that low-income countries are more prone to civil conflict than richer countries (Fearon and Laitin, 2003; Collier and Hoeffler, 2004). While it is tempting to explain this correlation with the argument that people living in low-income countries face a lower opportunity cost of organizing a rebellion, Fearon (2008) notes that the effect of income on unrest is ambiguous, because in low-income countries also the loot for which the rebels fight is small; this should also reduce the incentives to rebel. Chassang and Padró i Miquel (2009) qualify this conclusion, and show that temporary negative income shocks can increase the chances of revolt, while permanent income shocks have an ambiguous effect.

Much of the recent empirical literature on social unrest has focused on exogenous income shocks and their effects on conflict. Miguel, Satyanath and Sergenti (2004) find that adverse weather shocks significantly predict civil conflict in Africa, while Bohlken and Sergenti (2010) present similar results for Hindu-Muslim riots in India. Brückner and Ciccone (2010) show that downturns in international prices of the main commodity exported by Sub-Saharan countries lead to higher chances of civil war. Ponticelli and Voth (2011), looking at cross-country evidence for period 1919 to 2008 argue that episodes of fiscal consolidation lead to social turmoil. These results support the predictions of the model of Chassang and Padró i Miquel (2009) about the effects of temporary income shocks. Relatedly, Autor *et al.* (2016) show that adverse trade shocks have led to more political polarization in U.S. constituencies.

We also contribute to the literature on the 'Captain Swing' riots. Systematic analysis began with the Parliamentary Inquiry that followed the unrest (Checkland, 1974). It largely blamed them on failings of the Poor Law. The Hammonds (1987) famously attributed the riots to growing immiserization of laborers in the countryside. Hobsbawn and Rudé compiled the first systematic database on the riots, and argued

[1] During the Industrial Revolution, new technologies may have been more skill-replacing than skill-biased (James and Skinner, 1985; Mokyr, 1992). The direction of technical change itself may be endogenous to factor prices (Acemoglu, 2002 and 2007). This would be in line with the early adoption of coal engines England (Allen, 2009) and the introduction of new machines for treating non-U.S. cotton during the U.S. Civil War (Hanlon, 2015).

that they were largely driven by the adverse effects of technological change. Stevenson (2013) emphasized that the riots were often aimed at Irish migrant workers, and not technology (see also Mokyr, Vickers and Ziebarth, 2015). Hobsbawn and Rudé’s database was extended by Holland (2005), and their analysis updated by Griffin (2012). Aidt and Franck (2015) have recently argued that the riots contributed to the 1832 Reform Act. Finally, Aidt, Leon and Satchell (2016) analyse how riots spread across England during the two years of unrest, and argue that “contagion” played a significant role.

Relative to the existing literature, we make the following contributions: First, we unify the literatures on technological change and on the economic determinants of conflict, by providing evidence for an additional channel – the distributional effect of the new technology. The current literature on income and conflict typically focuses on negative shocks (either temporary or permanent). New technologies represent a positive shock to output but create distributional effects that may affect some groups adversely. Threshing machines are labor-saving and reduce the share of output going to labor; this lowered rural workers’ opportunity cost of revolt. Second, we focus on a massive, rapid dislocation in the labor market driven by technological change. Threshing was the main income source for agricultural laborers for many months of the year. Steam or water threshing largely eliminated winter earnings for agricultural laborers, who constituted the relative majority of the labor force in most English counties (Shaw-Taylor *et al.* 2010). This is in contrast with more recent cases of technological change, which involve relatively gradual changes affecting a smaller part of the labor force (such as telephone operators or secretaries). Third, the introduction of threshing machines was skill-replacing, not skill-using. While not a highly complex task itself, the introduction of steam threshers resulted in the replacement of experienced men by women and boys. This is in contrast with more recent cases of technology adoption, which typically increase demand for high-skilled jobs (Autor, Katz and Krueger 1998).

We proceed as follows. Section 1 summarizes the historical background. Section 2 presents our data. Section 3 reports our main empirical results. Section 4 discusses mechanisms and examines some of the consequences of the riots. Section 5 shows the robustness of our results. Section 6 concludes.

1 Historical Background

Threshing is a key agricultural activity since humans domesticated plants. After the harvest, and before processing the cereals, farmers have to loosen the grains from the husks (threshing), and then separate the husks from the grains (winnowing). Performed by hand, threshing is a laborious process. Typically, hand-threshers used flails – two sticks connected by a short chain – that were swung overhead into a pile of grain. Manual threshing provided employment during winter, when there were few other work opportunities. In 1786, the Scottish engineer Andrew Meikle invented the first threshing machine (Macdonald, 1975). In this section, we sketch English agriculture in 1800, and discuss the link between this new machine and the 1830 riots.

a. Agriculture in early 1800 England

In contrast to most European countries, 1800 English agriculture was highly efficient and almost completely commercialized. The largest landowners, often noblemen, rarely took an active role in agriculture: most of the time they rented their land to a class of farmers-tenants (Hobsbawm and Rudé, 2014). These tenants used the most advanced techniques of the time: they regularly rotated crops, allowed either one year of fallow every three, or planted turnip and clover after two consecutive years of cereal cultivation (Rahm, 1844). They also fertilized abundantly their fields, rented agricultural machines and hired rural workers on local labor markets and fairs. At the end of the season, they sold most of the output on the market.

Agricultural laborers were at the bottom of the social pyramid: they were often illiterate and owned few assets. Since the end of 1600, they progressively lost access to common lands – first via the "yeoman's enclosure" (Allen 1992) and then through the wave of parliamentary enclosures of the 18th century (Neeson, 1996; Mingay, 2014). Additionally, population growth made their employment less certain. In the 18th century, large estates employed agricultural servants year-round: these servants typically began work in their teens, and were required to stay celibate (Voigtländer and Voth, 2013). By the early 1800s, population growth made this type of employment less common, and most agricultural laborers worked under temporary contracts. They prepared the fields during spring, and harvested the crops during summer, usually under piece-work contracts signed by the day, by the week or at most by the season (Thompson, 2013; Hobsbawn and Rudé, 2014). During winter, when agricultural work was scarce, many of them found employment as "threshers".[3]

[3] The Hammonds cite a landowner from Canterbury as saying that in his parish, "…where no machines had been introduced, there were twenty-three barns… in these barns fifteen men at least would find employment threshing corn up till May." (Hammond and Hammond 1987). Clark (2001) estimates that threshing accounted for up to 50 percent of winter income of rural laborers.

Another aspect that contributed to the hardship of rural laborers was low labor mobility. This was the result of a system of social insurance known as the "Poor Laws," which granted income support to the *impotent poors*.[4] Under these laws, parishes had to support every resident who applied for relief, but had no obligation towards people coming from elsewhere. (Marshall, 1977; Boyer 1990). This discouraged migration even over short distances and exacerbated the effects of population growth (Redford, 1976).[5]

Threshing machines spread from the beginning of 1800. They offered significant labor savings, as they allowed to thresh between 5 and 10 times faster than flails (Appendix B). Productivity gains depended on the specific type of machine however, and hand-powered machines offered hardly any saving.[6] In contrast, threshing machines moved by horses or water increased productivity by a factor of 5 and 10 respectively. Whenever available, water was the preferred source of power, as it also saved on fodder and animal supervision.[7] Beyond cost savings, machines offered other important advantages, as they could thresh an entire harvest in few weeks (Hobsbawm and Rudé, 2014) and produced less wastage (Hammond and Hammond 1987).

Threshing machines spread relatively slowly after their invention, as they were too expensive relative to manual labor (Hobsbawm and Rudé, 2014; Macdonald, 1975). However, when Great Britain and France went to war in 1803, the British Army and the Royal Navy inducted many rural workers (Colley, 2009). As rural labor became scarce, farmers adopted a number of labor-saving technologies, including threshing machines (Dickson and Stevenson, 1815). At the end of the war in 1815, Britain discharged most of its soldiers and rural labor became relatively abundant

[4] Elisabeth I introduced the Poor Law in 1601 with the "Acte for the Reliefe of the Poore" (Marshall, 1977). The basic framework remained in place until 1834 (Boyer, 1990, Clark and Page, 2008).

[5] Boyer (1990) argues that the Poor Law did not slow down aggregate rural-urban migration. His conclusion does not exclude the possibility that the Poor Laws prevented rural-rural migration, and Landau (1995) presents evidence that the "Laws of Settlement" systematically limited migration across parishes in the 18th century.

[6] We estimate productivity of machines with information from the General Views of Agriculture of all English counties. In these volumes, we only found two hand-powered threshing machines, both in Berkshire (Mavor, 1813). On the first, the informant observes that: "This machine in its present form is evidently more curious than useful. Without horses it is impossible to produce a saving." About the second, he notes: "The only saving Mr. Tull finds in its use is in making reed for thatching."

[7] The "threshing machines" entry of *Farmers' Encyclopedia* states: "Where the locality admits the use of a water wheel, this power is most economical and easily managed; but the advantage is limited to peculiar situations." (Johnson, 1844).

again. Nonetheless, threshing machines remained in use and continued to spread, possibly because they allowed farmers to thresh grains quicker, and bring their product to the market before prices dropped (Hobsbawn and Rudé, 2014).

b. Captain Swing riots

The 'Swing' riots broke out at the end of August 1830, in Kent.[9] They spread first to the South-East of England, and then across the country. By the winter of 1832, more than 3,000 riots had broken out in 45 different counties. Almost all of these episodes took place in rural areas: in all cases, rioters were rural workers, sometimes led by local craftsmen (Hobsbawn and Rudé, 2014; Stevenson, 2013). The first protests saw rioters breaking agricultural capital, especially threshing machines: between September and November 1830 Holland (2005) lists 529 threshing machines attacked.

Unrest took several forms. Arson attacks were common (Tilly, 1995) and in many parishes rioters forced the overseers of the poor out of the parish. Wage negotiations occurred frequently, with farmers agreeing to a minimum wage under the condition that tithes and rents were reduced commensurately (Griffin 2012; Hammond and Hammond 1987). Threatening letters – signed by the mythical 'Captain Swing' – were sent to farmers. These letters caught the public imagination, and by October 1830 *The Times* began to call 'Swing' the whole wave of riots (Griffin, 2012). Unrest simmered for more than two years, until the winter of 1832.

After an initially timid response, the government adopted the hard line and ordered the army and local militias to quell the protest. It also set up a special commission; this commission initially passed 252 death sentences, but eventually commuted most of them into oversea transportation (Hobsbawn and Rudé, 2014).

c. Causes of unrest

Several factors contributed to the wave of riots in 1830-32. Hobsbawn and Rudé (2014) emphasize how bad weather, a poor harvest and the prospect of a cold winter made the already difficult situation of rural workers unsustainable. The year 1830 also saw an increase in political agitation as well as discussions of electoral reform. Against the background of the July revolution in France, agitators like William Cobbett toured the countryside, arguing for the need of change, a living wage, and a rebalancing of power (Wells 1997; Dyck, 2005). News of the French and Belgian revolutions may have provided the spark that ignited the revolt in Kent (Archer, 2000;

[9] Hobsbawn and Rudé (2014) place the start of the riots on the 28th of August 1830, when a gang of people smashed a threshing machine in Lower Hardres, Kent. Recently, Griffin (2012) demonstrated that riots began 4 days earlier, when 20 men destroyed the first threshing machine in Elham, Kent.

Charlesworth, 1979). In addition, discussions of electoral reform had come to naught under the Duke of Wellington's Tory government. They would eventually lead to the Great Reform Act of 1832 under his liberal successor – but only after Wellington's government fell during the worst period of the riots (Aidt and Franck 2015). Once the revolt had started, riots spread to the rest of the country, often as a result of bands of workers travelling from parish to parish to exact justice on the landlords (Tilly, 1995) or following the accounts of incidents in nearby parishes reported by "linkmen" travelling along the major roads (Archer, 2000; Aidt *et al.*, 2016).

Whatever the immediate motives of the riots, historians agree that the underlying cause of unrest was a progressive deterioration of the economic and social situation of rural workers. Three factors contributed to the decline. First, since the end of 1600 the enclosure movement had progressively deprived rural workers of access to common lands, effectively transforming them into a "landless proletarian, relying almost exclusively on wage-labor" (Hobsbawn and Rudé, 2014; Hammond and Hammond, 1987). Second, bringing in the harvest in cereal-producing areas required a large workforce – but employment opportunities were scarce during the rest of the year. The Poor Laws allowed to maintain a sufficient number of agricultural laborers year-round, but they had come under considerable strain since the beginning of 1800 because of population growth and the decline of cottage industry (Stevenson, 2013). As an increasing number of poors claimed relief, allowances were reduced and workers became increasingly dissatisfied with the system (Thompson, 2013).

Finally, the progressive mechanization of agriculture made redundant much of the agricultural labor force and undermined its standard of living. The adoption of threshing machines was especially harmful for rural workers because it deprived them of the major source of income during the winter season. To illustrate the impact of the new machines on the rural labor market, we combine data on threshing machine diffusion in 1800-1830 (described in the next section), with information on rural unemployment in 1834 (Checkland, 1974). Each threshing machine in a parish was associated with 2 percent higher winter unemployment. In contrast, summer unemployment was essentially unaffected by machines (β = -0.001, p = 0.868). If we consider the difference between winter and summer unemployment, we find that the presence of threshing machines is associated with significantly more winter unemployment. To illustrate, unemployment was on average 5.5 percent higher in winter than in summer, but the presence of one threshing machine increased this difference by 2.1 percentage points. Columns 1-3 of Table 1 show that this positive association survives the inclusion of controls and substantiate the claim that threshing machines increased winter unemployment.

While enclosures, poor laws and mechanization appear in almost any account of the Swing riots, historians disagree on their relative importance. Thompson (2013) and Royle (2000) emphasize the role of enclosures and the loss of access to land. The Parliamentary enquiry, set up after the 1830-32 riots, largely blamed the "Old Poor Law" – soon to be reformed thoroughly. Finally, Hobsbawn and Rudé (2014) insist on the importance of the new machines.

2 Data

In our main analysis, we combine data on the location of all Swing riots with original, hand-collected data on threshing machines adoption in England during the first three decades of 1800. We complement this information with data from the 1801 crop returns, from the 1821 British Census and from the 1832 report of the Poor Law Commission, as well as estimated climatic conditions in England at the beginning of the 19th century. Additionally, our identification strategy predicts the adoption of threshing machines using local land characteristics. Here, we describe each of these sources; details about individual variables are in appendix A.

Data on Swing riots come from a database compiled by the Family and Community Historical Research Society, a group of researchers coordinated by Holland (2005).[10] The data contain a comprehensive list of Captain Swing incidents between August 1830 and December 1832. The information comes mainly from official records of judicial courts that investigated these incidents, but it is integrated with accounts reported in newspapers of the time. The database provides the date, the parish, and the type of crime perpetrated by rioters. It builds on Hobsbawm and Rudé (2014), adding a further 1642 riots to their original list of 1475 incidents. Some of the riots during the years 1830-32 are particularly relevant for our paper: these are the direct attacks on threshing machines. Figure 2 reports the total number of Swing riots over time, broken down by "attacks on threshing machines" and all other events. Figure 3 shows the geographical distribution of these incidents.

To track the adoption of threshing machines before the riots, we combine information from two separate sources. The first are farm advertisements that appeared on 60 regional newspapers (57 from England and 3 from Wales). The second are the "General Views of Agriculture," a collection of surveys that analyzed

[10] Aidt and Franck (2015) use these data in their study of the political consequences of Swing riots.

English agriculture between 1790 and 1820. We collect farm advertisements from the universe of 118,758 newspaper issues published between January 1800 and July 1830: within each of these issues, we search for advertisements containing the exact string "threshing machine". These would typically announce the sale or the lease of a farm. Figure 4 and Figure 5 show two advertisements contained in our database. In order to assign these articles to different areas of Britain, we manually code the exact parish where the threshing machine was located. This results in a total of 549 advertisements in 466 parishes: Figure 6 reports the number of advertisements of threshing machines that appeared during the thirty years leading up to the Swing riots.

We complement this initial set of machines with information from the "General View of Agriculture". The General Views are a series of surveys sponsored by the Board of Agriculture: each volume covers a single county, and reports on a standardized set of agricultural topics. The first editions of these surveys appeared in the 1790s and were followed by second editions during the 1810s. We find few references to threshing machines in the early editions; however, by 1810 threshing machines were so widespread that every volume devotes to these machines an entire chapter. Each of these chapters report on several threshing machines: for each of them, the surveyor discusses technical characteristics, including productivity, and provides information on the owner and location of the machine. We code the location of each of the machines mentioned in these chapters. When possible, we use the additional information to estimate the productivity of these machines (see Appendix B). Figure 7 shows the geographical distribution of threshing machines.

To predict threshing machines adoption, we use two geographical characteristics that influence the profitability of the new technology: terrain features that allow to install water mills and soil suitability to wheat cultivation. To quantify the suitability of an area for water-mill operation, we use the *accumulation flow*. This variable is part of the HydroSHEDS database (Lehner, Verdin and Jarvis, 2008) and captures the amount of upstream area that drains into each cell of a global, 15 seconds grid. HydroSHEDS calculates accumulation flow as number of upstream cells, and higher values of accumulation flow are a strong predictor of the presence of a river. Figure 8 shows the accumulation flow in Britain. In the empirical section, we argue that this measure is a significant predictor of the presence of water mills.

We source data on soil suitability to the cultivation of wheat from the Global Agro-Ecological Zones database (FAO-GAEZ). These data report the potential output that can be harvested in a given area by cultivating wheat. FAO researchers compute this potential output by using soil characteristics, historical weather records and an agronomic model that assumes the use of a specific level of inputs.[12] These measures are available for grid cells of about 9.25 × 9.25 kilometers. We construct a measure of potential output at the parish level by superimposing a map with the boundaries of historical British parishes on the grid of soil suitability, and then computing the average yield attainable in every parish. Figure 9 shows the potential output for wheat in Britain.

We also collect new data on the generosity of poor relief at the parish level from the Poor Law Commission Report (Checkland, 1979). For a subsample of 1333 parishes, the Report records poor rates collected in 1803, 1813, 1821 and 1831 and population in census years (1801, 1811, 1821 and 1831). From this data, we measure generosity of poor relief by dividing the poor's rates collected in 1803 by the 1801 population (see Figure 10 for an example). While the two variables are recorded in different years, the variable has the advantage to be determined before threshing machines started to spread in England. On average, English parishes collected little less than 14 shillings per capita, with substantial variation – parishes at the 90th percentile collected 5 times as much as those at the 10th percentile.

We complement this information with the following sources. First, we use the 1821 British population census (Southall *et al.*, 2004), to reconstruct demographic and sectoral composition of each parish. Second, we use the 1801 corn returns (Turner, 1982), to calculate the acreage cultivated with different crops at the beginning of 1800. Third, we use tables in Gonner (1912) to reconstruct the advancement of enclosures until the year 1820. Fourth, we use data from Luterbacher *et al.* (2004) and Pauling *et al.* (2006) to reconstruct yearly weather across England and Wales for the years 1800-1830. We use these data to calculate how much 1830 temperature and precipitation deviated from their 1800-1828 averages. We also use FAO-GAEZ data to estimate suitability of land to the growth of grass and the map of Caird (1852) to divide England in 4 regions. Finally, we calculate distances using the coordinates of parish centroids, which we compute using a map of parishes from 1851 (Burton, Southall, Westwood and Carter, 2004). Table 2 reports summary statistics for our variables and Appendix A describes each variable.

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[12] FAO-GAEZ calculates potential output under three different assumption of input use: "low", "intermediate" and "high". We use the measure of potential output calculated with "intermediate input" because it is likely to represent well the technologies available to 1800s British farmers. See Bustos, Caprettini and Ponticelli (2016) for a discussion about the different technological levels used in FAO-GAEZ measures. See section 5.a for a more complete discussion of this assumption.

3 Empirical analysis

a. Threshing machines and riots

We start by documenting the correlation between adoption of threshing machines in the first three decades of the 1800s and the riots of 1830-32. The aim of this section is to establish that in places where threshing machines spread faster, also experienced more protest in 1830-32.

Panel A of Figure 1 illustrates our main finding. We divide English parishes into two groups — those with and without evidence of threshing machine adoption. Parishes with at least one advertisement for a threshing machine pre-1830 had 26 percentage point probability of seeing at least one riot – almost twice the likelihood of parishes with no ads. Next, we show that this basic relationship holds in a setting with a richer set of controls. We estimate variations of the following regression:

$$Riot_p = \beta_0 + \beta_1\, Machines_p + \beta_{pop}\, Pop1821_p + \beta_X\, X_p + e_p \qquad (1)$$

Where $Riot_p$ is the number of riots in parish p during 1830-32, $Machines_p$ is the number of threshing machines, *Pop1821* is the (logarithm of the) total population living in the parish in 1821, and X_p is the vector of additional parish-level characteristics. These include: the (logarithm of the) area of the parish; the share of families that are chiefly employed in agriculture in 1821; the (logarithm of the) male-female ratio in 1821; the (logarithm of the) distance to Elham, the parish where Griffin (2012) records the first riot and the (logarithm of) the distance to the closest city that prints one newspaper.

The area of the parish allows us to control for another dimension of size apart from the population. The share of agricultural families proxies for the degree of agricultural specialization in the parish: this has the potential to affect riots, because Swing was almost exclusively a rural phenomenon. The relative presence of men over women could also affect the emergence of riots, which in most cases were a men’s affair (Stevenson, 2013: p. 268).[14] The distance to the location of the first riot allows us to account for possible contagion across parishes affected by the riots (Aidt, Leon and Satchell, 2016). Finally, controlling for distance to the closest city that printed a newspaper is important because the collection of data on both threshing machines and riots partly relies on information reported in newspapers. Thus, parishes that are

[14] In the data of Holland (2005) there are 21 women out of 1566 rioters prosecuted (1.34 percent).

closer to the place of publication of a newspaper may have better news coverage of farm advertisements, and they may end up having more riots recorded in our database.

In the most demanding specification, we include fixed effects for the 4 macro-regions of England plus one additional region corresponding to Wales. We define these regions following a map of Caird (1852), who divides England along two lines: one running North-South and another East-West. The North-South line separates agricultural areas mainly specialized in dairy production (in the West) from areas mainly specialized in cereal production (in the East). The East-West line divides areas where agricultural labor was relatively scarce and wages relatively high from areas where the opposite was true. These regressions identify the relationship between threshing machines and riots within geographical units with relatively homogeneous agricultural systems. With these fixed effects regression (1) becomes:

$$Riot_p = \beta_0 + \beta_1 \, Machines_p + \beta_{pop} \, Pop1821_p + \beta_X \, X_p + \theta_r + e_p \qquad (2)$$

presents our results. The dependent variable is always the number of Swing riots. Column 1 reports the estimates of equation (1) when we control only for the 1821 population in the parish: here the coefficient on $Machines_p$ is positive and significant ($p < 0.001$). Adding other parish-level controls in column 2 reduces the point estimate slightly but does not affect significance ($p < 0.001$). Column 3 adds the 5 region fixed effects: point estimate falls only slightly and significance remains high ($p = 0.001$). This last result underscores that the correlation between machine adoption and riots is strong even within homogeneous agricultural regions.

In the last two columns of Table 3 we consider two alternative explanations for the Swing riots. First, Hobsbawn and Rudé (2014) note that the years 1828-30 had wet summers and poor harvests. Additionally, the autumn of 1830 was cold and they report stories of people being “afraid of the winter”. These observations suggest that weather shocks may have contributed to the outbreak of the riots in the fall of 1830. Second, Thompson (2013) and Royle (2000) emphasize the role of enclosure in impoverishing rural workers in the decades leading to the riots. To account for these two potential channel we include four additional controls. We construct 3 historical weather variables: abnormal precipitation in spring and summer of 1830 and abnormal temperature in the fall of 1830. We also collect a measure of share of land enclosed before 1820. Because this latter variable is available only for little more than 7,000 parishes, we lose about 30 percent of our observations in these last two regressions. Column 4 of Table 3 reports the estimates of equation (1) when we include these additional 4 variables, while column 5 reports estimates of equation (2) with region fixed effects. In both cases the coefficient on threshing machines remains positive and significant: if anything the association between machines and riots becomes stronger.

The number of Swing riots in a parish is a count variable, and almost 86 percent of the parishes do not experience unrest during 1830-32. The nature of this variable implies that a simple linear model may not provide the best fit to our data, so in Table C2 in the appendix we show that our results are robust to alternative estimation methods. In columns 1 through 6 of Table C2 we replicate Table 2 when the dependent variable is a dummy equal to 1 for every parish that experiences at least one riot. In column 1 through 3 we fit a linear probability model, while in columns 4 through 6 we fit a probit model. In all specifications, the effect of threshing machines is positive and significant at the 0.1 percent or better. In columns 7 through 9 we estimate equations (1) and (2) with a Poisson regression. Also with this specification the number of threshing machines is positively and significantly related to riots: the *p*-value is lower than 0.001 when we control for population, it grows to 0.003 when we add parish-level controls and to 0.044 when we include region fixed effects.

The results of this section point to a strong and positive correlation between riots and adoption of the new machines. The strength of these results is noteworthy because our measure of technology adoption is necessarily noisy. It is very likely that we mis-classify numerous parishes where threshing machines were in operation but were not reported on newspaper advertisements nor in the General Views. This will bias our estimates downwards (Deaton, 1997: p.99). We therefore think of the coefficients in Table 3 as lower bounds of the true effect.

b. Identification

The results in the previous section point to a strong relationship between adoption of threshing machines and Swing riots. Nevertheless, there are three reasons why this relationship may not be causal. First, reverse causality may bias estimates downwards. This would happen if landlords and farmers were less inclined to adopt labor-saving technologies where the risk of protest was high. Anecdotal evidence from the period suggests that this is a valid concern.[15] Second, there may be omitted variables that affect both the adoption of labor-saving technologies and the likelihood of rural protest. While the inclusion of observed characteristics did not affect point estimates in Table 3, it is still possible that other, unobserved characteristics correlate with both

[15] For instance Caird (1852) talks of an Oxfordshire farmer who "had so many hands thrown upon him, that he resorted to spade husbandry, being the best means in which they could be employed".

technology adoption and riots. This would also bias our estimates. Third, measurement error in technology adoption is likely to bias estimates downward, because we do not observe all threshing machines in use between 1800 and 1830.

To address these issues we need plausibly exogenous variation in the adoption of threshing machines. Finding exogenous determinants of machine adoption is complicated by the fact that at the beginning of 1800, threshing machines came in many different shapes and forms. In particular, three different sources of power were commonly used to move threshing machines: man-power, horses and water-mills.[16] The difference between these power sources makes it challenging to find a variable that affects the diffusion of every type of threshing machines and that at the same time is excluded from equation (1). In order to make progress, we decide to focus on the diffusion of a single type of threshing machines: those powered by water.

While water-powered threshing machines represented only part of all threshing machines in 1830,[17] there are three reasons to focus on them. First, whenever available, water provided energy that was cheaper than any other alternative, an advantage of which contemporary observers were well aware. We expect that, whenever English farmers had the possibility to install a water-mill, they would prefer water over any alternative source of energy. Second, not only did water machines rely on cheaper energy, they also allowed greater labor savings than either man- or horse-powered machines. With water power, men or women were only needed to feed cereals into the machine — an activity that was required also with all other types of machines. In Figure B1 in Appendix B, we show that water-powered threshing machines saved twice as much labor as horse-powered threshing machines and more than 10 times as manual threshing. Because water machines offered greater scope to save labor, we also expect them to have greater impact on the riots. Third, the possibility to install a water-mill was determined by conditions outside the control of local farmers, so we use these conditions to produce an instrument excluded from equation (1).

To capture water-power availability, we use information about the strength of streams as measured by the average accumulation flow in a parish. We expect

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[16] We find no evidence of steam-powered threshing machines in any of the primary sources produced before 1830. They never appear in the General View of Agriculture, nor on newspaper articles. We interpret this evidence as an indication that steam-powered threshing machines were uncommon in the years before the riots.

[17] In the General Views of Agriculture, all published before 1816, we can determine the power source for 91 of the 118 threshing machines mentioned: of these, 10 percent were moved by a water-mill.

accumulation flow to predict the adoption of water-powered threshing machines, because this measure directly determines the strength and the course of streams and rivers. The presence of streams and rivers is in turn essential to power water mills.[18]

The second variable we use to predict adoption is soil suitability for wheat cultivation, which measures how much wheat farmers can expect to harvest if they decide to cultivate this crop. We expect wheat suitability to predict the adoption of the new technology because farmers used threshing machines almost exclusively to thresh wheat.[20] We measure wheat suitability with FAO's potential yield data for this crop, using intermediate inputs.

As an instrument for adoption, we use the product of accumulation flow and wheat suitability. In all regressions we control separately for accumulation flow and wheat suitability, and maintain that when we do so, the product of the two is excludable from equation (1). Controlling for accumulation flow and wheat suitability separately is important because either of these two variables may affect riots through channels different from machine adoption. For example, the possibility to install a water-mill may promote the development of activities that rely on the mill, and these may have a direct effect on unrest. Similarly, wheat suitability may encourage specialization in wheat production, and this in turn may result in organization of labor different from the one that emerges in pastoral areas. Because the way labor is organized may have a direct effect on unrest, wheat suitability may not be excluded from equation (1).

In contrast, when we control for accumulation flow and wheat suitability separately, the product of the two is unlikely to affect unrest except through the adoption of water-powered threshing machines. Because we include wheat suitability in the regressions, we effectively compare parishes that have the same potential to grow wheat, and we ask what is the effect of also being able to install a water-mill. Because before the arrival of threshing machines wheat production did not rely on

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[18] We validate this argument with data from the website "Mills Archive" (https://millsarchive.org/). The website lists more than 11000 mills, mostly in England. We identify and geo-locate 6620 mills operated by water: these mills were not necessarily used to power threshing machines, although some were. The log of accumulation flow is a very significant predictor of the presence of a water mill in a parish: when we regress the presence of a water mill the *t*-statistics of the log accumulation flow ranges between 15 and 19, depending on the estimation method. These results are available upon request.

[20] Hobsbawm and Rudé (2014) state that 'oats and barley were definitely cheaper to thresh by hand.'

water power, this circumstance had no effect on agriculture before the machines arrived.[21]

Table 4 supports these claims. In this table, we look at parish characteristics observed before the riots, and regress them on accumulation flow, wheat suitability and the product of the two. The interaction term does not correlate with most of these pre-determined characteristics. We show the strongest result on the first column of the table. Here, we report the estimates when the dependent variable is the share of agricultural land cultivated with wheat in 1801, a year in which threshing machines were almost absent in England.[22] The coefficient of the interaction between accumulation flow and wheat suitability is small and not significantly different from zero. This result substantiates our claim that the possibility to install water-mills did not make wheat cultivation more attractive before the arrival of threshing machines.

Table 4 also shows that our instrument is significantly correlated with the population living in the parish in 1821 (column 2). To alleviate the concern that this correlation with parish size is driving the results, we control for 1821 population in all specifications. In particular, in column 3 we show that when we control population the interaction of accumulation flow and wheat suitability still does not predict the share of land cultivated with wheat in 1801. The remaining columns of Table 4 show that the instrument is not significantly correlated with the area of the parish (column 4), and with the sex ratio in 1821 (column 5). Column 6 shows that the share of workers employed in agriculture is positively correlated with the instrument, and the relationship is significant at the 10 percent level. Overall, these results support the validity of our identification strategy, as they suggest that prior to the riots and prior to the diffusion of the machines, parishes with identical wheat suitability did not differ systematically when they also had the possibility to install a water-mills.

c. First Stage: Predicting Threshing Machines Adoption

We start by documenting the unconditional relationship between our measure of threshing machine adoption and the two variables we expect to capture its profitability: accumulation flow and potential yield of wheat. We do this in panel A and B of Figure 11. In the upper part of panel A, we plot a local polynomial of the

[21] Accumulation flow does not capture the potential for irrigation, and indeed a variable constructed from the river network is a weak predictor of machine adoption. The existence of river is not sufficient to install a water-mill, which also requires the water to flow with enough speed and mass rate.

[22] The General Views of Agriculture for the counties of Bedfordshire, Norfolk and Hampshire compiled in the 1790s have no mention of threshing machines. Threshing machines are mentioned only in the Scottish counties of Aberdeenshire and Banffshire (Anderson, 1794; Donaldson, 1794).

average number of threshing machines observed in a parish (on the y-axis) against the log accumulation flow (on the x-axis).[23] In the upper part of panel B we repeat the exercise but substitute the accumulation flow with the log of the potential yield of wheat. The figures show that the relationship between threshing machines and accumulation flow is an inverse-U shape, although estimates are noisy for high levels of this variable. They also suggest that threshing machines are more common in places where wheat brings richer harvests. These relationships are tightly estimated especially in the parts of the distributions where we have a greater number of parishes, as the frequency distributions on the bottom panels of the two figures reveal.

These graphs confirm the existence of a relationship between the adoption of threshing machines and both potential yield of wheat and accumulation flow. However, because neither of these two variables are likely to be excluded from equation (1), they are not valid instruments for threshing machine adoption. Our identification strategy relies on the assumption that, once we control for wheat and accumulation flow separately, the *interaction* between these two variables is excluded from the structural equation (1). This strategy requires this interaction to predict the diffusion of threshing machines in the years before the riots. We confirm that this is the case by estimating the following model:

$$\begin{aligned} Machines_p &= \alpha_0 + \alpha_1 \log acc_p \times Yield^{wheat}{}_p + \\ &\alpha_2 \log acc_p + \alpha_3\, Yield^{wheat}{}_p + \alpha_{pop} \log Pop1821_p + \alpha_X X_p + \psi_r + u_p \end{aligned} \qquad (3)$$

In equation (3) we regress the number of threshing machines in parish p ($Machines_p$), on the logarithm of the accumulation flow ($\log acc_p$), the potential yield of wheat ($Yield^{wheat}{}_p$), and the interaction between these two variables. In the simplest specification, we control for total number of people living in the parish in 1821. We then add a vector of controls that includes area of the parish, the sex ratio, the share of agricultural families, the distance to the closest town that publishes a newspaper, distance from the first riots and a measure of how easily grass grows in the parish. In the most demanding specification, we add 5 region fixed effects (ψ_r). This allows us to estimate the effect of our instrument within homogeneous agricultural areas.

The first column of Table 5 reports the estimates of equation (3**Error! Reference source not found.**) when we only control for the 1821 population. The coefficient of the interaction is positive and significant, with an F-stat of 9.5. In the

[23] To produce this figure, we use the Epanechnikov kernel function and a bandwidth of 0.198 (a value calculated with the “rule of the thumb” formula).

second column, we add the other parish-level controls: in this regression, the point estimate remains stable and highly significant ($F = 9$). In the third column, we add the fixed effects for the 5 regions of England and Wales. In this regression, the coefficient of the interaction becomes slightly larger and significance increases: in this specification the F-stat is 17.4, well above the critical value of 10 suggested by Stock and Yogo (2002). These results suggest that the interaction of wheat and water mill suitability significantly predicts the diffusion of threshing machines, and we can use it as an instrument. Because in some of these specifications the F-stat of the excluded instrument is slightly below 10, we will report the Rubin-Anderson statistics, which is robust to weak instruments (Stock, Wright and Yogo, 2002 and Anderson and Rubin, 1949).

d. Reduced Form: Riots and Determinants of Machine Adoption

We now move to the study of the determinants of riots. We start by discussing the results of the reduced form: the direct relationship between accumulation flow and wheat suitability and the outbreak of Swing riots. Because the geographical characteristics that determine land suitability are beyond the control of 1800s farmers, these estimates identify the causal effect of being located in an area that allows water mill operation and is suitable to wheat cultivation. In the analysis, we control separately for the baseline effects of water mill and wheat suitability, effectively comparing areas with the same potential wheat output, and estimating the additional effect of having the possibility to install a water mill. Our identification strategy hinges on the assumption that once we control for the baseline water mill and grain suitability, the ability to operate a water mill affects the likelihood of observing riots *only* because it induces farmers to adopt the new technology.

Before presenting our econometric results, we start with a visual illustration of our findings. Figure 12 reproduces our measure of wheat suitability shown in Figure 9, and overlays the location of all the Swing riots episodes. In this map, black dots identify parishes with Swing riots, and we draw larger dots in parishes where Holland (2005) records more episodes. The map shows that across England and Wales, riots concentrated at the intersection of the counties of Wiltshire, Berkshire and Hampshire, in the South-Eastern counties of Kent and Sussex, and in the Eastern county of Norfolk. These regions are also the ones that are more suitable to wheat cultivation, according to the FAO-GAEZ data. Figure 12 also displays significant variation within areas with relatively homogeneous wheat suitability: our identification strategy exploits this heterogeneity by allowing the effect of wheat suitability to differ in places with and without the possibility to install a water mill. Figure 13 illustrates. On the left the figure reproduces the map of wheat suitability and Swing riots shown on Figure 12. On the right, it shows three panels that magnify three areas of the map. In this panels we show the location of the riots and the log accumulation flow in the background. On the whole, Figure 13 suggests that while these three areas had relatively homogeneous wheat suitability, they were quite heterogeneous in terms of accumulation flow. They also suggest that riots in these areas concentrated disproportionally along those canals where more water drains, and water mills are easier to operate.

Next, we proceed to present our results in a regression framework. We fit the following model to the data:

$$\begin{aligned} Riot_p &= \gamma_0 + \gamma_1 \log acc_p \times Yield^{wheat}{}_p + \\ &+ \gamma_2 \log acc_p + \gamma_3\, Yield^{wheat}{}_p + \gamma_{pop} \log Pop1821_p + \gamma_X X_p + \eta_r + \nu_p \end{aligned} \tag{4}$$

In (4), we regress the number of Swing riot on the explanatory variables included in the first stage regression (3). The coefficient of interest is γ_1, which captures how much the interaction between water mill and grain suitability drove unrest, after accounting for the baseline effect of both.

Columns 4 through 6 of Table 5 show the estimates of equation (4). When we only include the 1821 parish population in column 4, we find a positive and significant coefficient on the interaction term, indicating that areas with greater wheat suitability saw more unrest when they also offered the opportunity to install water mills. When we add other parish-level characteristics on column 5 the precision of the estimates improves, as the standard error of the interaction term drops by almost 40 percent. However, the point estimate of the interaction term remains very stable: this confirms that our instrument is uncorrelated with other observable characteristics. In column 6 of Table 4 we add the 5 region fixed effects: this improves the precision of our estimates further, but leaves the point estimate unaffected.

On the whole, these results point to a strong and robust relationship between our excluded instrument and the diffusion of riots. The interaction between water mill and grain suitability always predicts more riots, and it is always significant ($p < 0.001$). Moreover, the point estimate of the instrument remains stable across specifications: this gives us confidence that the instrument is uncorrelated with other unobserved characteristics that may be driving the riots.

e. Two-Stage Least Squares

In columns 7 through 9 of Table 5 we turn to the two-stage-least-squares estimates. In all regressions we control separately for wheat suitability and the log accumulation flow, and instrument the number of threshing machines advertisements with the interaction between these two variables. In column 7 we start by controlling for the number of people living in the parish in 1821: in this specification the coefficient of our measure of technology adoption is positive and significant ($p < 0.001$). When we add other parish-level controls on column 8 the coefficient drops slightly, but maintains significance ($p < 0.001$). Finally, when we estimate the effect within the five agricultural regions of England in column 9 we find a similar point estimate that remains significant at less than 0.1 percent level.

The point estimate on column 9 of Table 4 suggests that places that were induced to install one extra machine because of their land characteristics experienced on average 4.8 more riots during 1830-32. This is a sizeable effect, larger than the effect we find with OLS in Table 3. To make sense of these magnitudes, we start by breaking down riots into two categories: the first with all riots that involved the attack of a machine, and the second with every other violent event.[24] We use these two separate variables to re-estimate the two-stages least squares. We report the results in Table 6. In column 1 through 3 we show the estimates when the dependent variable is the number of attacks on threshing machines, while in column 4 through 6 we look at all other episodes. Estimates from the first 3 columns suggest that one extra threshing machine led to 0.7 more attacks on machines. Columns 4 through 6 suggest that the effect was larger for other types of protest: a parish with one extra machine saw around 4 more riots. These results suggest that machines worked as catalyst of protest, as the presence of one extra machine led to five more protests that were not directly aimed at the machine. Moreover, we find it comforting that in the first three columns we do not find a coefficient that is significantly larger than 1.

These results suggest that the OLS estimates are downward biased. There are two reasons why in this setting a downward bias is reasonable. First, reverse causality is likely to bias estimates downward, because farmers who live in more unstable places should be less inclined to adopt a technology that was very unpopular among rural workers. Second, the noise in our measure of machine adoption is also likely to bias OLS estimates downward. This happens because, as we only count machines publicized on local newspapers, we are certain to miss many. Calling $TrueMachines_p$ the true measure of machines in parish p, we only observe $Machines_p = \pi\ TrueMachines_p$, for some $\pi < 1$. Thus, if β^*_1 is the true effect of *TrueMachine* on *Riot*, equation (1) will estimate a smaller coefficient $\beta_1 = \beta^*_1 \times \pi$. We can assess the strength of this bias by looking once more at protests that targeted threshing machines. For

[24] Around 17 percent of all episodes involved the destruction of threshing machines.

these episodes, we are certain that a machine was present at the time of the riot, and we can ask how often we also observed a machine from our newspapers. We observe attacks on machines in 320 separate parishes; only 11 percent (36) of these parishes appeared in advertisements publicizing the sale of one of these machines. These figures suggest that OLS estimates may underestimate the true effect of machines on riots by almost 90 percent. This would explain between 70 and 40 percent of the difference between OLS and two-stage least squares estimates.

4 Mechanisms and consequences

In this section, we examine the channels that led from technology adoption to unrest. We document that in areas where machines appeared together with other factors that impoverished rural workers, the relationship between technology adoption and riots was stronger. In contrast, in areas where other factors dampened the adverse effect of mechanization, technology adoption was not associated with riots. We conclude with a note on the effect of riots on subsequent innovation and technology adoption.

a. Manufacturing Employment

We start with the role of alternative occupations. Labor-saving technologies do not have to lead to social unrest if displaced workers can find alternative employment easily. In 1830s, many towns were thriving, either as centers of manufacturing or from trade and services. Because rural workers who migrated to these cities could find employment with relative ease, we expect rural workers living in areas close to manufacturing centers to respond to the introduction of new labor-saving machines by migrating. In these areas, the introduction of threshing machines should engender less opposition, resulting in less unrest during the Swing riots.

Table 7 confirms that this is the case. For each parish in England, we compute the distance to the closest of 15 manufacturing centers. We then split the sample into above-median and below-median distance from one of these centers.[30] On Panel A of Table 7 we report OLS estimates of equation (2) on these two subsamples. Columns 2, 5 and 8 show that adoption of threshing machines is associated with significantly more riots in the 5,049 parishes that lie far away from one of these manufacturing centers. In contrast, the relationship is not significantly different from 0 for the other

[30] The 15 manufacturing centers are in Gloucestershire, Lancashire, Middlesex (London), Norfolk, Warwickshire and Yorkshire, West Riding. See appendix for details. The median parish is Winchfield in Hampshire which lies 62 Km from London.

half of the sample. The coefficients are significantly different from each other in all specifications.

Panel B of Table 7 turns to the reduced form: here having the possibility to install a water-mill in a wheat-producing area leads to significantly more unrest in parishes that are far away from a manufacturing center (columns 2, 5 and 8), but not in those that lie closer to them (columns 3, 6 and 9). Again, the coefficients are different from each other with a confidence of $p = 0.12$ or better. Overall, these results suggest that wherever moving to the cities and working in the manufacturing sector was a viable option, the introduction of labor-saving agricultural technology was associated with less resistance than in places where workers had no alternative occupation. Proximity to a larger town is clearly related to many aspects of agricultural production and the interaction of city proximity with unrest is undoubtedly complex. For this reason, we see the evidence in this subsection as only suggestive that urban labor markets reduced instability by offering an "escape valve" for surplus labor after the introduction of labor-saving technology.

b. Enclosures

We turn now to the role of enclosures. Neeson (1996) and Mingay (2014) emphasize the importance of enclosures in limiting the access of land to rural workers, and Thompson (2013) and Royle (2000) argued that these were one of the major causes of the 1830 riots. In section 2.a we show that controlling for enclosures strengthens the association between machines and riots: here, we ask whether the presence of enclosures amplified the effect of machines on riots.

Enclosures redistributed the ownership of common land from the rural community to few large landlords (Mingay, 2014). In turn, labor-saving technology redistributes output from labor to the owners of other factors of production, especially capital. In areas in which large parts of agricultural land are still in commons, workers may benefit from the introduction of labor-saving technology because they still hold small stakes in another factor of production: land. In contrast, where most land is enclosed, workers only contribute to production with labor. In these cases, labor-saving technologies are especially harmful to them, as the reduction of the labor share is not compensated in any other way. Thus, we expect a high level of enclosures to exacerbate the effect of machines on riots.

Table 8 presents evidence consistent with this intuition. As we did for distance to manufacturing cities, we split the sample of parishes into two groups. The first group has all parishes where enclosures are higher than the median parish. The second one contains the other half, where enclosures were less widespread.[31] Panel A of Table 8 replicates OLS regressions: we estimate equations (1) and (2) first on the full sample (in columns 1, 4 and 7), and then on the two samples with high (columns 2, 5 and 8) and low (columns 3, 6 and 9) enclosures. In all specifications, the relationship between machines and riots is strong and precisely estimated in the sample of parishes where enclosures are widespread. In contrast, we find no significant association between machines and riots in the group of parishes where few enclosures. The coefficients of the threshing machine variable in the two samples are significantly different from each other (p = 0.07 or better). Panel B of Table 8 estimates the reduced form regression in the same three samples of panel A. Also in these regressions, we find a significant correlation between riots and our instrument in the sample of parishes that had a high level of enclosures already in 1820. While the difference between the coefficients in the two samples is not significant, the relationship between riots and the determinants of machine adoption is noisy and unstable in the sample of parishes with few enclosures. Overall, the evidence in this section provides suggestive evidence that enclosures exacerbated the effect of machines on riots.

c. Generosity of Poor Relief

We conclude with the role of redistribution. New technology typically represents a net gain to society. One important policy question is thus whether workers can be 'bought off', accepting the adoption of new technology because redistribution guarantees a minimum living standard. We use new data on the local generosity of poor relief to examine this question.

We use the Poor Law Report (Checkland, 1979) to assemble a new database of poor law generosity, defined as poor rates per capita in 1801-3 at the parish level.[32] We have valid information on poor relief for a total of 1,333 parishes across England, and we split this sample in two, using the parish with the median poor rate per capita.[34] Next, we estimate both OLS regression (2) and reduced form (4) on both

[31] We only observe enclosures for registration districts, and parishes in the same district share the same value of enclosure. The median parish is in the districts of Biggleswade (Bedford), Billericay, Colchester, Ongar, Romford (Essex) and Market Harborough (Leicester), where 1 percent of commons was enclosed. There are 107 parishes in these districts, and we assign them to the 'low' enclosure group: this is the reason why splitting parishes at the median does not produce two samples of exactly the same size.

[32] The Report records poor rates for 1803 and population for 1801 (from the population census).

[34] The median parish is Doddington in Cambridgeshire, which collects and redistribute £0.6 per capita.

subsamples separately. Table 9 reports our results. Panel A reports OLS estimates: for the sample of non-generous parishes with poor relief below the median on columns 2, 5 and 8, and for the other half of generous parishes, in columns 4, 6 and 9. For the small sample of parishes for which we have data on poor relief generosity we have low power, and we find a significant relationship between machines and riot only in the specification without region fixed effects. Within this sample however, the strongest effect comes from the parishes that have low poor relief: for this group the coefficient of machines is positive and much larger than the one for the group of generous parishes. Despite lack of power we also find relatively low *p*-values for these estimates, which are significantly different from 0 at the 8.5, 11.4 and 12.9 percent.

In Panel B of Table 9, we turn to the reduced form, and show that in parishes with above-average poor relief, the effect of our instrument on unrest is muted. While places with more watermill suitability and better cultivation conditions for wheat are more likely to see unrest in 1830, the relationship is stable and precisely estimated only in the subsample of parishes where the poor received little support. Where the poor laws offered generous support, wheat and water mill suitability do not predict riots. Overall, these results in this section provide tentative support for the idea that the effect of machines on riots appears to be driven by parishes that treated their poor poorly. Where new technology deprived laborers of their livelihood without a sufficient social insurance mechanism, unrest was the result.

d. Consequences: innovation and technology adoption 1832-1850

In this section, we take a look at some of the consequences of the 1830 protest. Aidt and Franck (2015) argue that the riots convinced part of the English *élite* to extend the franchise with the 1834 Great Reform Act. Here, we are interested in the impact of riots on a different outcome: innovative activity. Hobsbawn (1952) suggests that in the areas that saw the most intense riots, threshing machines disappeared in the years following the revolt. Given the attention that rioters gave to new technology, it is important to determine whether farmers and entrepreneurs were so impressed by the revolt that they felt discouraged to innovate or adopt new technology after the protest. If this was the case, the Swing riots would offer a cautionary tale of the dangers that unrestrained technical progress poses on one of its major forces.

To investigate the effect of riots on innovation we look at two different aspects of innovative activity: the invention of new technologies and their adoption. We proxy the location where new technologies were invented with the place of residence of every inventor who registered a patent in Britain in the years 1813-1843. This is collected from Woodcroft (1854), who provides a comprehensive list of patents registered in England between 1617 and 1852. For this analysis, we focus on the patents registered between 1813 and 1843. We measure adoption of new technologies with diffusion of agricultural machines in the years 1832-1850. We assemble this measure in a way similar to the one used to measure the diffusion of threshing machines before the riots. We first select 7 years between 1833 and 1853;[37] next, we look in the newspapers published in each of these years for the farm advertisements that mention "threshing machines," or "mowing machines." We complement the information on threshing machines with diffusion of mowing machines because the latter were extremely labor saving and started to spread in the years after the riots (Walton, 1973).[38] To study the effect of riots on innovative activity, we regress these variables on the distance to the closest machine broken during the Swing riots.

The first 4 columns of Table 10 report the results with invention. In all specifications we exclude urban areas and focus on rural parishes where riots were more likely to have had an impact.[39] The dependent variable is the number of inventors who registered a patent. On column 1 of Table 10 we show the unconditional relationship between inventors and distance to the closest machine broken during Swing. Places farther from one of these episodes were home of significantly more inventors in the 10 years following the riots (p = 0.057). On column 2 we control for inventive activity in the 10 years before the riots and find that distance to a machine attach is still positively and significantly associated with innovative activity after the riots (p = 0.028). When we add other parish-level controls on column 3 we still find a positive and significant effect (p = 0.019). Finally, adding 5 region fixed effects reduces significance, but the coefficient remains significantly different from 0 at the 10 percent level. The average parish in these regressions lies 13.2 Km from a Swing attack on a threshing machine: the estimate on column 4 of Table 10 implies that this parish would be home of 0.005 more inventors in the years 1832-1843 relative to a parish where workers destroyed one of these machines. This is equivalent to 31 percent of the average number of inventors in this sample of parishes.

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[37] We randomly select 1835, 1838, 1841, 1844, 1847, 1850 and 1853. We did not attempt to digitize every year due to time and financial constraints.

[38] Results with only threshing machine adoption are qualitatively similar and available upon request.

[39] This excludes 437 parishes within 10 Km from one of the 15 manufacturing centers used in section 4.a. Inventors living in these parishes registered 71 percent of patents in the years 1813-1829 and 75 percent of patents in the years 1832-1843.

We now turn to the association between riots and machine adoption. When it comes to the adoption of agricultural machines, there is one challenge to uncover the effect of riots. The challenge is that wheat-producing areas that adopted threshing machines in the first three decades of 1800 were also more likely to reintroduce these machines after 1830. We deal with this issue in two ways. First, we restrict attention to parishes within 35 kilometers from one of the threshing machines attacked during Swing. This effectively discard the North of England and Wales, and centers attention on the most important areas for cereal cultivation. Second, we control for the diffusion of machines between 1800 and 1830.

Columns 5 to 8 of Table 10 reports the results of this analysis. In all specification the dependent variable is the number of threshing machines and mowing observed in the years 1832-1853. In column 5 we show the unconditional correlation: this is positive and significant (p = 0.049). When we add controls for past adoption (column 6), parish characteristics (column 7) and region fixed effects (column 8) the coefficient remains unaffected and significance improves. The average parish in these regressions lies 13.6 Km from a Swing attack on a threshing machine: the estimates on Table 10 imply that this parish would adopt little more than 0.01 labor saving machines in the 20 years after the riots than the parish that experienced the attack. This is equivalent of about 22 percent of the average number of machines adopted between 1832 and 1853 (0.06). Overall, these results provide suggestive evidence that riots discouraged innovative activity in the years following the riots.

5 Robustness

In this section we show that our results survive a number of robustness checks.

a. Robustness: Definition of suitability to wheat production

Until now, we have used the potential yield for wheat as an indicator of the profitability of wheat cultivation across England. FAO researchers compute the potential yield using soil and weather characteristics, together with specific assumptions about the source of irrigation, input use and farm management (Fischer *et al.* 2011).[41] In our baseline results, we use potential yield attainable by rain-fed

[41] One possible concern with this measure has to do with the weather variables used to compute potential yield. FAO researchers use average weather conditions for the period 1961-1990, which may differ from weather condition at the beginning of 1800. We collect estimates of temperature and precipitation in England over the years 1801-1830. In Appendix C.1 we contrast these estimates with recorded temperature and precipitation during the years 1961-1990 and we show that weather conditions did not change significantly during this period.

agriculture with “intermediate-level inputs” and “improved management”. Under these assumptions, agricultural production is market oriented, farmers practice “adequate fallow” and rely on “manual labor with hand tools and/or animal traction and some mechanization” (Fisher *et al.*, 2011, p. 56). In addition, farmers plant the “improved varieties” of seeds that were in use before the Green Revolution of the 1940s (Gollin *et al.*, 2016), and apply “some fertilizer” as well as “pest, disease and weed control.” Most of these characteristics reflect English agriculture in early 1800, especially the kind of operations that would consider the adoption of the new threshing machines. Nevertheless, the assumption of fertilizers may be problematic, because it is possible that some of the chemical products considered by FAO researchers were not available to English farmers of the nineteenth century.[42]

To alleviate concerns that overestimation of potential yields is driving results, in this section we report results when we measure wheat suitability with the potential yield of wheat attainable with “low inputs”. The one advantage of this measure is that it is calculated assuming “no use of chemicals for pest and disease control”. Because this measure also considers a production process that was overall less advanced than the one common in 1800 English farms, it provides a lower bound for wheat productivity across England. Thus, these results should confirm that the variation that drives our results captures general suitability to wheat cultivation of different areas of England, and not the specific assumption regarding the input use.

We report our results on Table C3. We start in columns 1-3 with first stage estimates: as in our baseline results, the interaction between wheat suitability and accumulation flow is positive very significant in all specifications, with *F*-stats above the critical value of 10. We report the reduced form estimates in columns 4-6. Again, in all specifications the interaction maintains the same sign and significance as in the baseline results on Table 5. Moreover, point estimate remains stable as we add controls, suggesting that also this measure of wheat suitability is not correlated with other observable characteristics. Finally, we report two-stages least squares on columns 7-9. The effect of machines on riots remains positive and significant at less than 0.1 percent level in all specifications. Additionally, the point estimates are similar to our baseline estimates. Overall, these results confirm that our baseline results are not driven by the particular assumptions about the input use embedded in the FAO-GAEZ measure of potential yield.

[42] While English farmers would routinely use several types of manure such as chalk, marl, clay and excrements as fertilizers (Rahm, 1844), they did not have access to more recent chemical products.

b. Robustness: Spatial autocorrelation

In section 3, we base inference on conventional robust standard errors that do not account for spatial correlation in the explanatory variable. However, the geographic distribution of machines and riots, as well as water-mill and wheat suitability suggest that these variables vary smoothly over space, and that spatial correlation may be a concern. While spatial correlation does not invalidate identification, it does imply that robust standard errors may be biased. In this section we show that accounting for spatial correlation has no effect on our results.

We control for spatial correlation in two ways. First, we compute standard errors with the formula proposed by Conley (1999). In his model, Conley assumes that spatial correlation across locations decays with distance until a given cutoff. Since this cutoff is unknown and its choice arbitrary, we experiment with three different cutoffs: 20, 50 and 100 km. Second, we estimate standard errors in a non-parametric way, and cluster them at the level of the closest city that publishes a newspaper. This creates 60 separate clusters.

Table C4 reports the results. In columns 1-3 we report the OLS estimates of equations (1) and (2); and in column 4-6 the reduced form estimates. In each of these columns, we report the point estimates and the Huber-Eicker-White robust standard errors on the first two rows: these estimates are identical to those shown in Tables 3 and 5. Below these rows, we also report standard errors robust to spatial correlation: first the standard errors calculated with the Conley (1999) formula (on rows 3 through 5) and then those clustered at the level of the closest city with a newspaper. Results remain strong even when standard errors account for spatial correlation. In every OLS specification on columns 1-3 of Table C4, estimates remain very significant: spatially robust standard errors are up to a third higher than robust standard errors, but we can always reject the null of no significant correlation at the 0.6 percent or better. Similarly, all reduced form results survive when we account for spatial correlation: spatially robust standard errors tend again to be larger than conventional robust standard errors, but all estimates remain significant at the 2.8 percent level or better. All in all, these results suggest that the presence of spatial autocorrelation does not invalidate our inference.

c. Robustness: Sample restrictions

Part of the information we use to track machine adoption comes from historical newspapers. These newspapers circulated in 60 towns and cities, and they were more likely to advertise farm sales happening near the place of publication. Similarly, also the riot data may over-represent parishes around towns that published newspapers. In fact, although the core of the Swing riots database was compiled by Hobsbawn and Rudé (2014) from official probate records, Holland (2005) integrated this data with articles from local newspapers. This may introduce a spurious correlation between machines and riots driven by the distance to the closest newspaper. To control for this possible confounding mechanism, we include the distance to the closest newspaper in all our regressions. Additionally, here we show that all our results survive if we restrict the sample to parishes within 50 kilometers from the closest newspaper. We report our estimates on Table C5. This table show estimates for OLS (columns 1-2), first stage (columns 3-4), reduced form (columns 5-6) and two-stages least squares (columns 7-8). These estimates confirm that none of our results is driven by the uneven coverage of English parishes offered by 1800 newspapers.

A second concern with our results is that they reflect the contrast between English and Welsh parishes. English parishes specialized in cereal production and bore the brunt of the Swing riots. In contrast, pastoral agriculture was more common in Wales, and the riots left this region almost untouched. To address this concern, in all regression we show that our estimates are robust at including a set of five regions fixed effects: because one of these regions corresponds to Wales, these regressions exploit variation only *within* these separate regions. In addition, in this section we show that excluding the 949 Welsh parishes from our regressions strengthen all our results. These results are in Table C6 that report estimates for OLS (columns 1-2), first stage (columns 3-4), reduced form (columns 5-6) and two-stages least squares (columns 7-8). These estimates confirm that all our results are driven by variations *within* different areas of England.

A final concern has to do with the timing of the riots. While Holland (2005) records episodes that happened until the end of 1832, most of the protests took place in the winter of 1830-31 and the revolt was over by the spring of 1831. Because later episodes may connect to the initial revolt only weakly, their inclusion may introduce noise. To address this concern, we replicate the whole analysis after excluding all episodes that happened after April 1831.[44] Results are reported in Table C7 which shows estimates for the OLS (columns 1-3), the reduced form (columns 4-6) and the two-stages least squares (columns 7-9). This results confirms that also the specific definition of riots is not driving our results.

[44] This excludes 619 episodes, and leaves us with 2421 episodes.

6 Conclusions

In this paper, we revisit a canonical case of technology-induced social unrest – the "Captain Swing" riots of 1830-32. Using newly-compiled data on the diffusion of threshing machines, we first demonstrate that labor-saving technology was a key determinant of the probability of unrest, and that machine-breaking typically spilled over into general rioting. Based on data about soil suitability and suitability for water power, we also show that the link was causal, with areas exhibiting greater suitability for water power and wheat cultivation showing both greater adoption of threshing machines and markedly higher incidence of riots. While many factors probably contributed to the outbreak of unrest in England and Wales in 1830-32, we demonstrate a clear causal contribution of technological change to political conflict.

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FIGURES AND GRAPHS

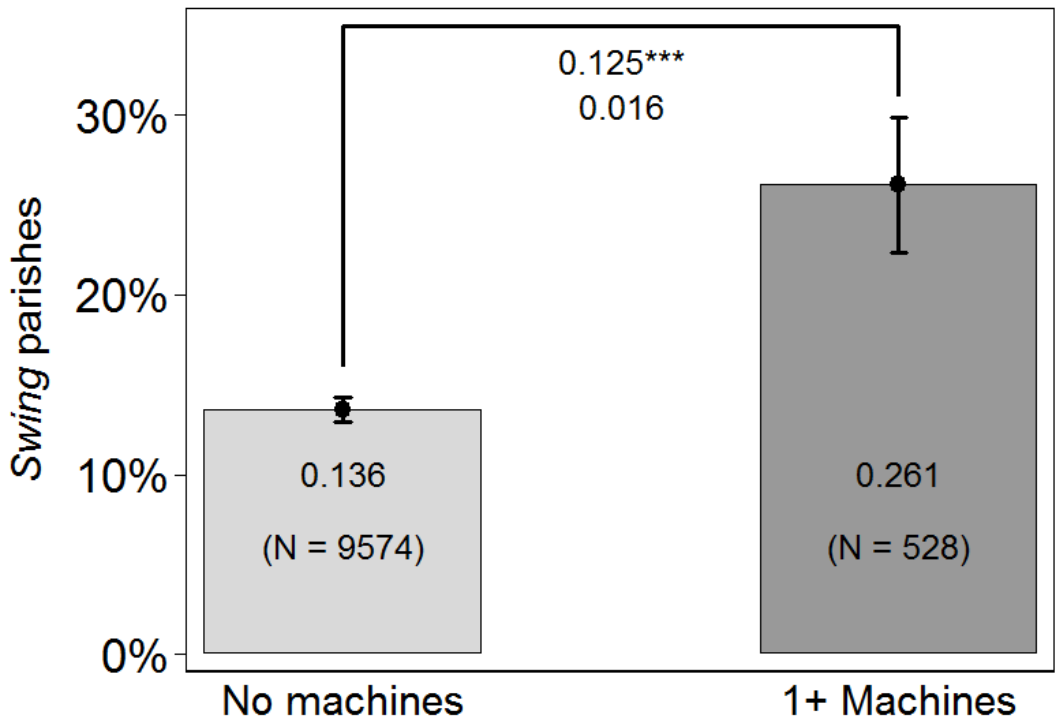


Figure 1. Panel A. Proportion of Swing riots, by whether a threshing machine was in use in the parish. Swing riots are all the riots in the Holland (2005) database of unrest events between August 1830 and winter 1832. The left bar is for parishes with no advertisements of a threshing machine between 1800 and 1830, as reflected in the British Newspaper Archive; the right column is for places with at least one advertisement during this period. Cf. Section 3 for details of data construction and Appendix A for variable definitions.

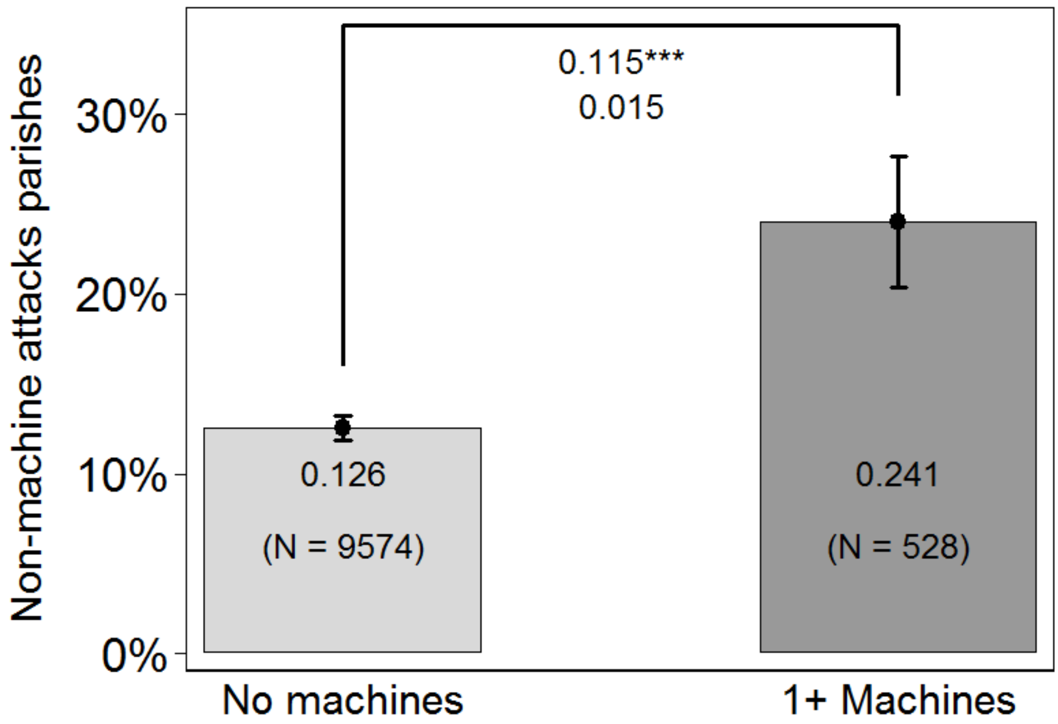


Figure 1. Panel B. Proportion of riots that did not involve the breaking of a threshing machine, by whether a threshing machine was in use in the parish. Swing riots are all the riots in the Holland (2005) which also classify the type of crime perpetrated by rioters. The left bar is for parishes with no advertisements of a threshing machine between 1800 and 1830, as reflected in the British Newspaper Archive; the right column is for places with at least one advertisement during this period. Cf. Section 3 for details of data construction and Appendix A for variable definitions.

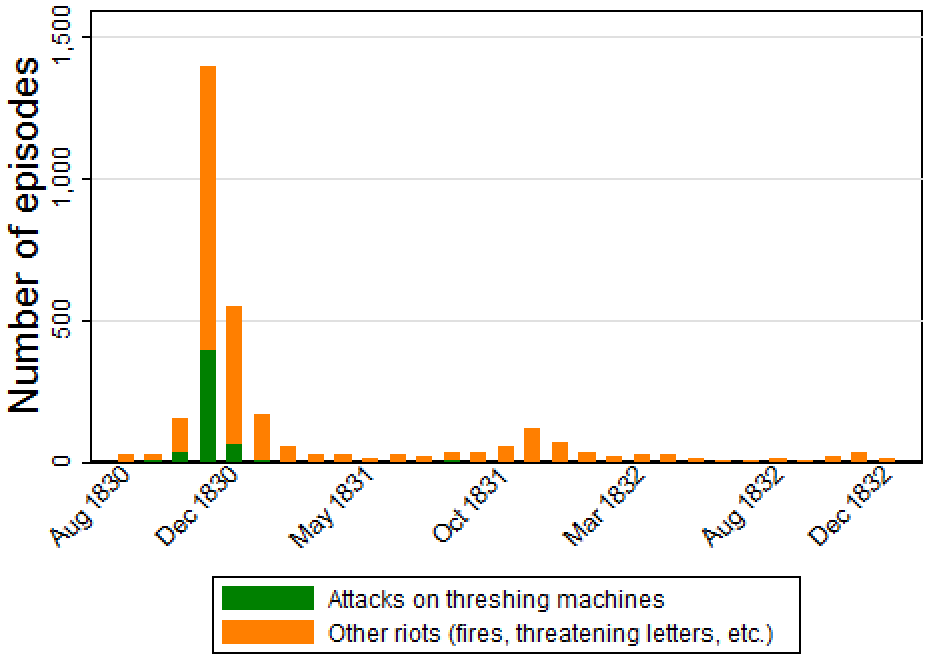


Figure 2. Number of episodes associated to the "Swing" riots. In green we plot the number of attacks on threshing machines. In orange, we plot all other riots that were associated to Swing: including threatening letters and fires. Source: Holland (2005).

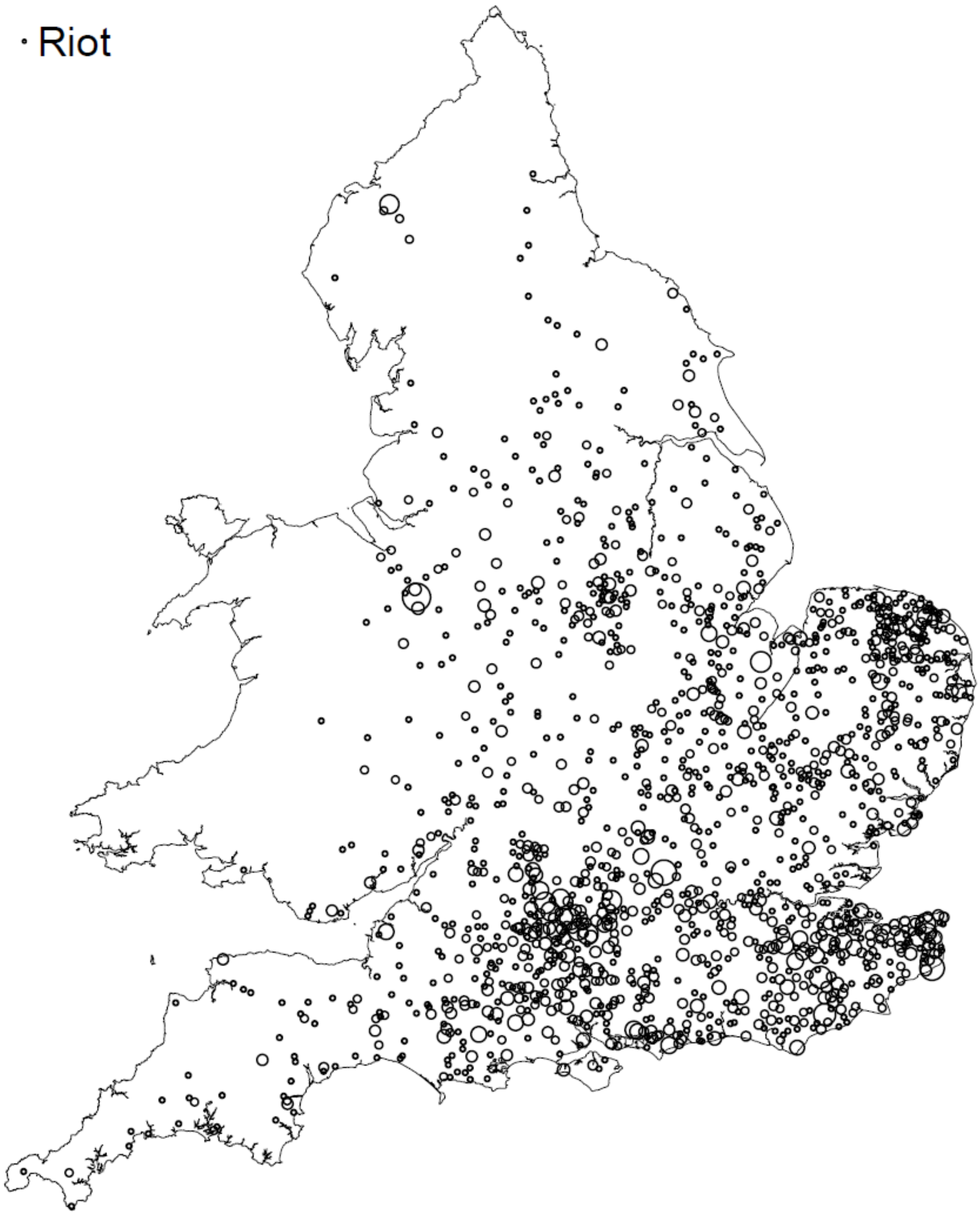
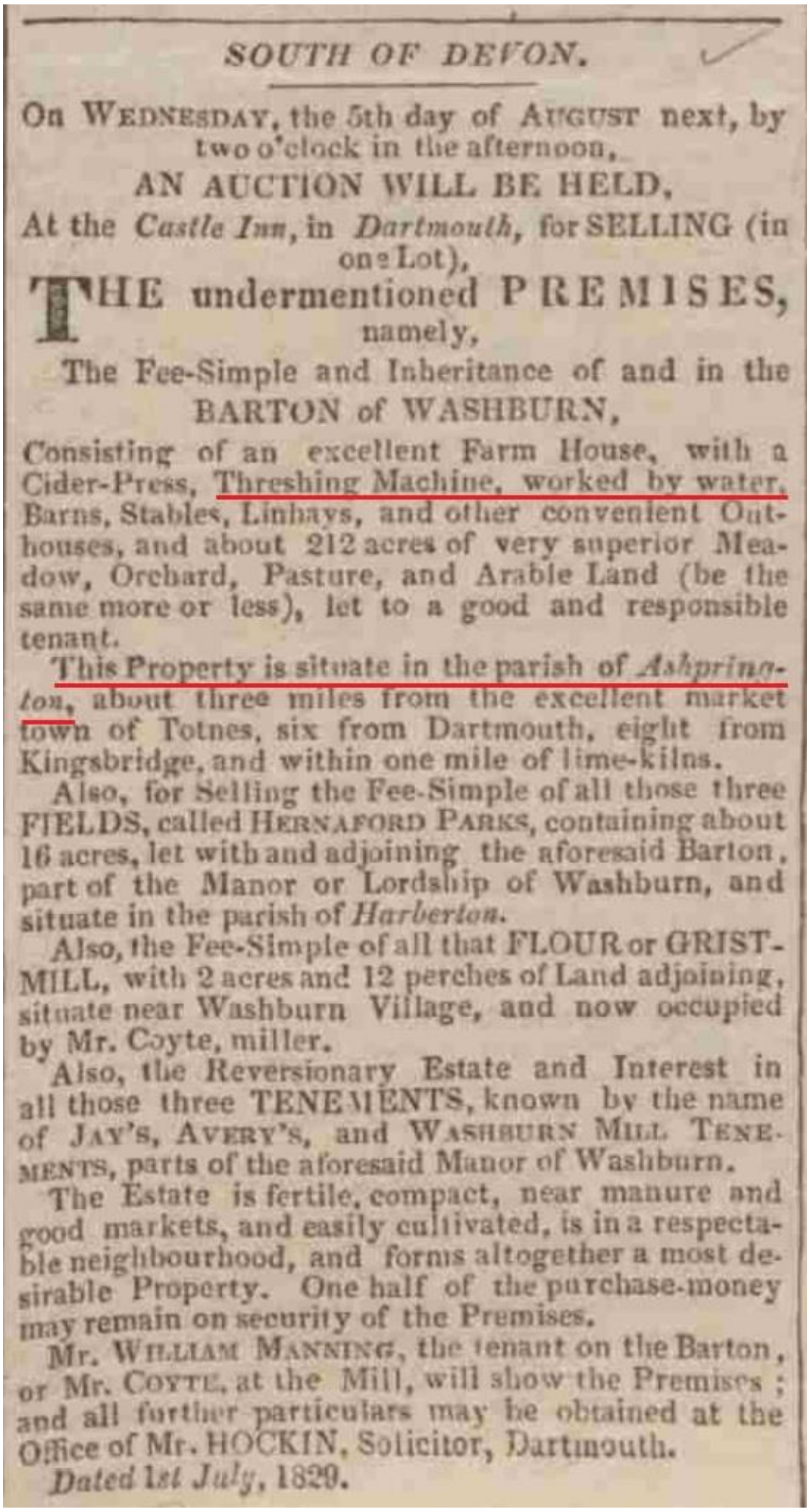


Figure 3. Geographical distribution of episodes associated to 'Swing' riots. Source: Holland (2005).



SOUTH OF DEVON.

On WEDNESDAY, the 5th day of AUGUST next, by two o'clock in the afternoon,

AN AUCTION WILL BE HELD,

At the *Castle Inn*, in *Dartmouth*, for SELLING (in one Lot),

THE undermentioned PREMISES, namely,

The Fee-Simple and Inheritance of and in the BARTON of WASHBURN,

Consisting of an excellent Farm House, with a Cider-Press, Threshing Machine, worked by water, Barns, Stables, Linhays, and other convenient Out-houses, and about 212 acres of very superior Meadow, Orchard, Pasture, and Arable Land (be the same more or less), let to a good and responsible tenant.

This Property is situate in the parish of *Ashprington*, about three miles from the excellent market town of Totnes, six from Dartmouth, eight from Kingsbridge, and within one mile of lime-kilns.

Also, for Selling the Fee-Simple of all those three FIELDS, called HERNAFORD PARKS, containing about 16 acres, let with and adjoining the aforesaid Barton, part of the Manor or Lordship of Washburn, and situate in the parish of *Harberton*.

Also, the Fee-Simple of all that FLOUR or GRIST-MILL, with 2 acres and 12 perches of Land adjoining, situate near Washburn Village, and now occupied by Mr. Coyte, miller.

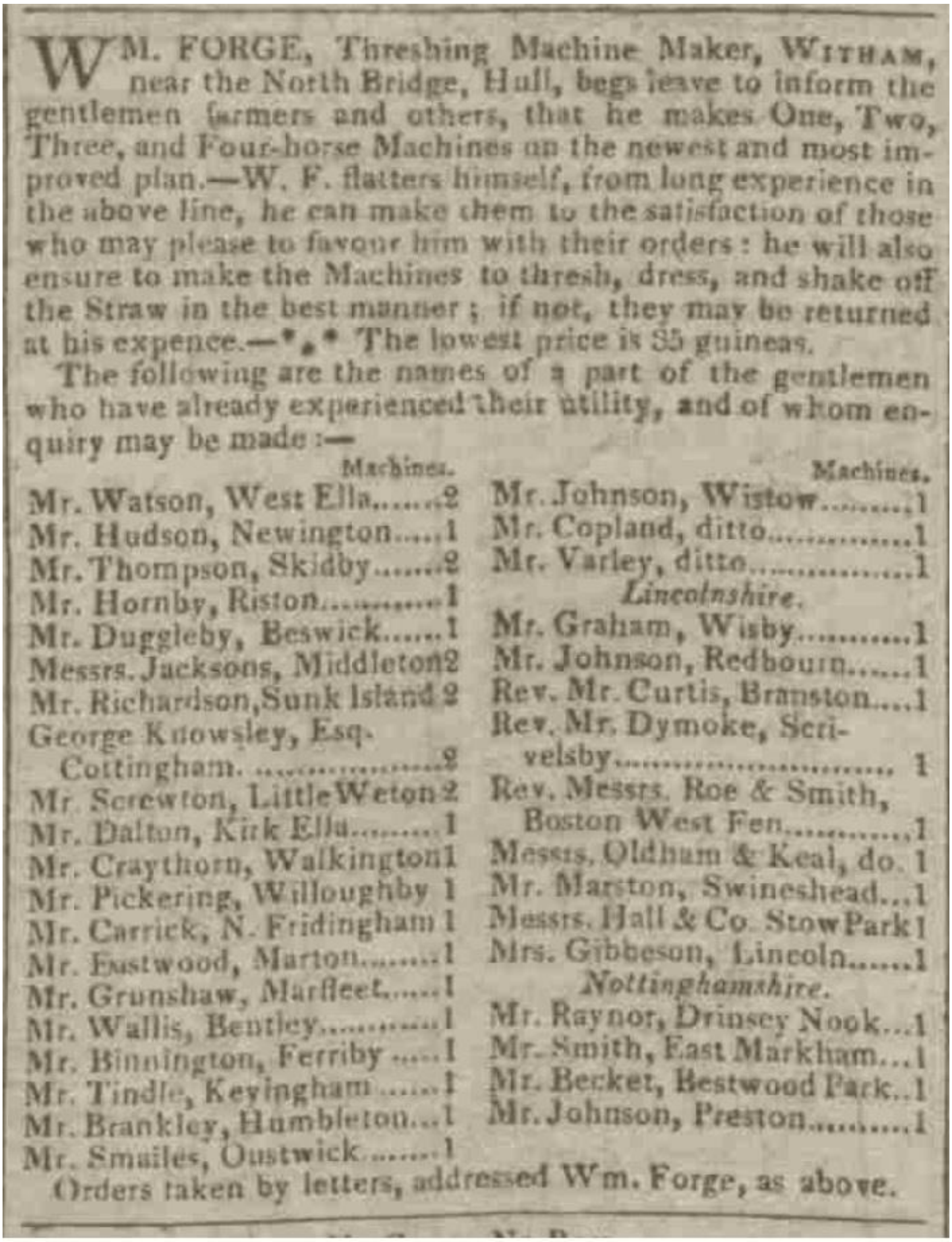
Also, the Reversionary Estate and Interest in all those three TENEMENTS, known by the name of JAY'S, AVERY'S, and WASHBURN MILL TENEMENTS, parts of the aforesaid Manor of Washburn.

The Estate is fertile, compact, near manure and good markets, and easily cultivated, is in a respectable neighbourhood, and forms altogether a most desirable Property. One half of the purchase-money may remain on security of the Premises.

Mr. WILLIAM MANNING, the tenant on the Barton, or Mr. COYTE, at the Mill, will show the Premises; and all further particulars may be obtained at the Office of Mr. HOCKIN, Solicitor, Dartmouth.

Dated 1st July, 1829.

Figure 4. Example of an advertisement for a "threshing machine". On July the 1st, 1829, the *Sherborne Mercury* advertised the sale of a farm in the parish of Ashprington (Devon). We count this advertisement as an indication that threshing machines are used in this parish because the farm includes a "threshing machine" among the assets that went on sale. Source: The British Newspaper Archive.



WM. FORGE, Threshing Machine Maker, WITHAM, near the North Bridge, Hull, begs leave to inform the gentlemen farmers and others, that he makes One, Two, Three, and Four-horse Machines on the newest and most improved plan.—W. F. flatters himself, from long experience in the above line, he can make them to the satisfaction of those who may please to favour him with their orders: he will also ensure to make the Machines to thresh, dress, and shake off the Straw in the best manner; if not, they may be returned at his expence.—*** The lowest price is 35 guineas.

The following are the names of a part of the gentlemen who have already experienced their utility, and of whom enquiry may be made:—

	Machines.
Mr. Watson, West Ella	2
Mr. Hudson, Newington	1
Mr. Thompson, Skidby	2
Mr. Hornby, Riston	1
Mr. Duggleby, Beswick	1
Messrs. Jacksons, Middleton	2
Mr. Richardson, Sunk Island	2
George Knowsley, Esq. Cottingham	2
Mr. Screwton, Little Weton	2
Mr. Dalton, Kirk Ella	1
Mr. Craythorn, Walkington	1
Mr. Pickering, Willoughby	1
Mr. Carrick, N. Fridingham	1
Mr. Eastwood, Marton	1
Mr. Grunshaw, Marfleet	1
Mr. Wallis, Bentley	1
Mr. Binnington, Ferriby	1
Mr. Tindle, Keyingham	1
Mr. Brankley, Humbleton	1
Mr. Smailes, Oustwick	1

	Machines.
Mr. Johnson, Wistow	1
Mr. Copland, ditto	1
Mr. Varley, ditto	1
Lincolnshire.	
Mr. Graham, Wisby	1
Mr. Johnson, Redbourn	1
Rev. Mr. Curtis, Branston	1
Rev. Mr. Dymoke, Scrivelsby	1
Rev. Messrs. Roe & Smith, Boston West Fen	1
Messrs. Oldham & Keal, do.	1
Mr. Marston, Swineshead	1
Messrs. Hall & Co. Stow Park	1
Mrs. Gibbeson, Lincoln	1
Nottinghamshire.	
Mr. Raynor, Drinsey Nook	1
Mr. Smith, East Markham	1
Mr. Becket, Bestwood Park	1
Mr. Johnson, Preston	1

Orders taken by letters, addressed Wm. Forge, as above.

Figure 5. Example of an advertisement. On February the 2nd, 1808, the *Stamford Mercury* published the notice of William Forge, a threshing machine maker, that advertised his product by suggesting to contact one of his past customers. We code each of the parishes listed above as parishes in which at least one threshing machine is in operation. Source: The British Newspaper Archive.

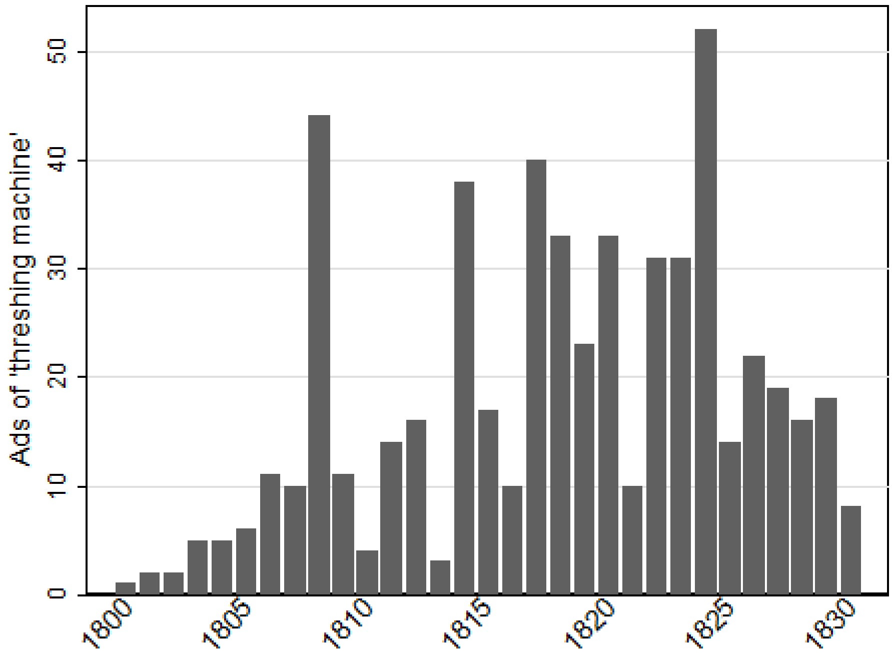


Figure 6. Number of advertisements for "threshing machines" that appeared on British newspapers: 1800-1830. Source: The British Newspaper Archive.

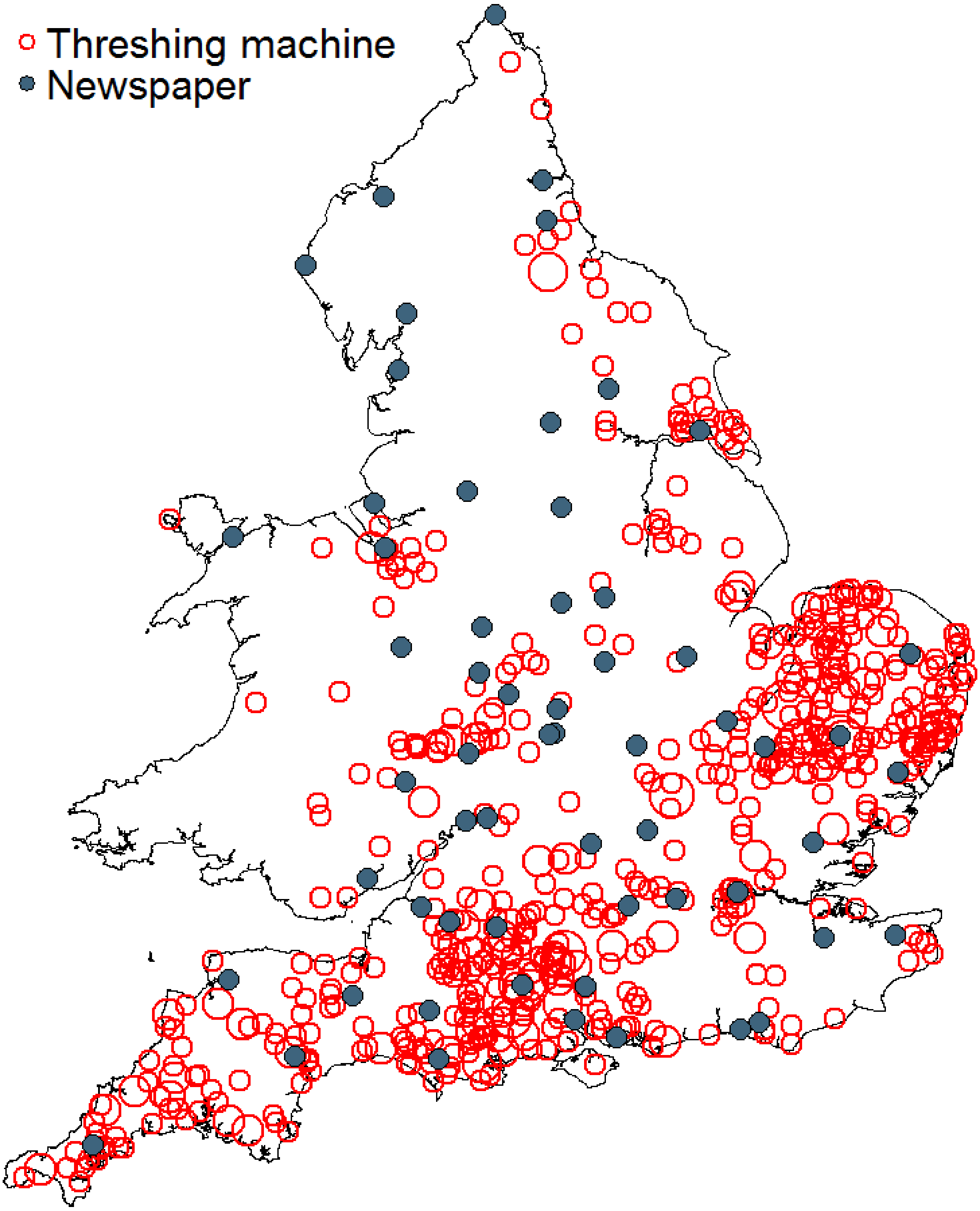


Figure 7. Geographical distribution of the advertisements for "threshing machines" published by British newspapers: 1800-1830. Red dots identify parishes with threshing machines, and dots are drawn so that they are proportional to the number of threshing machine we find in a given parish. Blue dots identify cities that printed at least one of the newspaper from which we collect our advertisements. Source: The British Newspaper Archive.

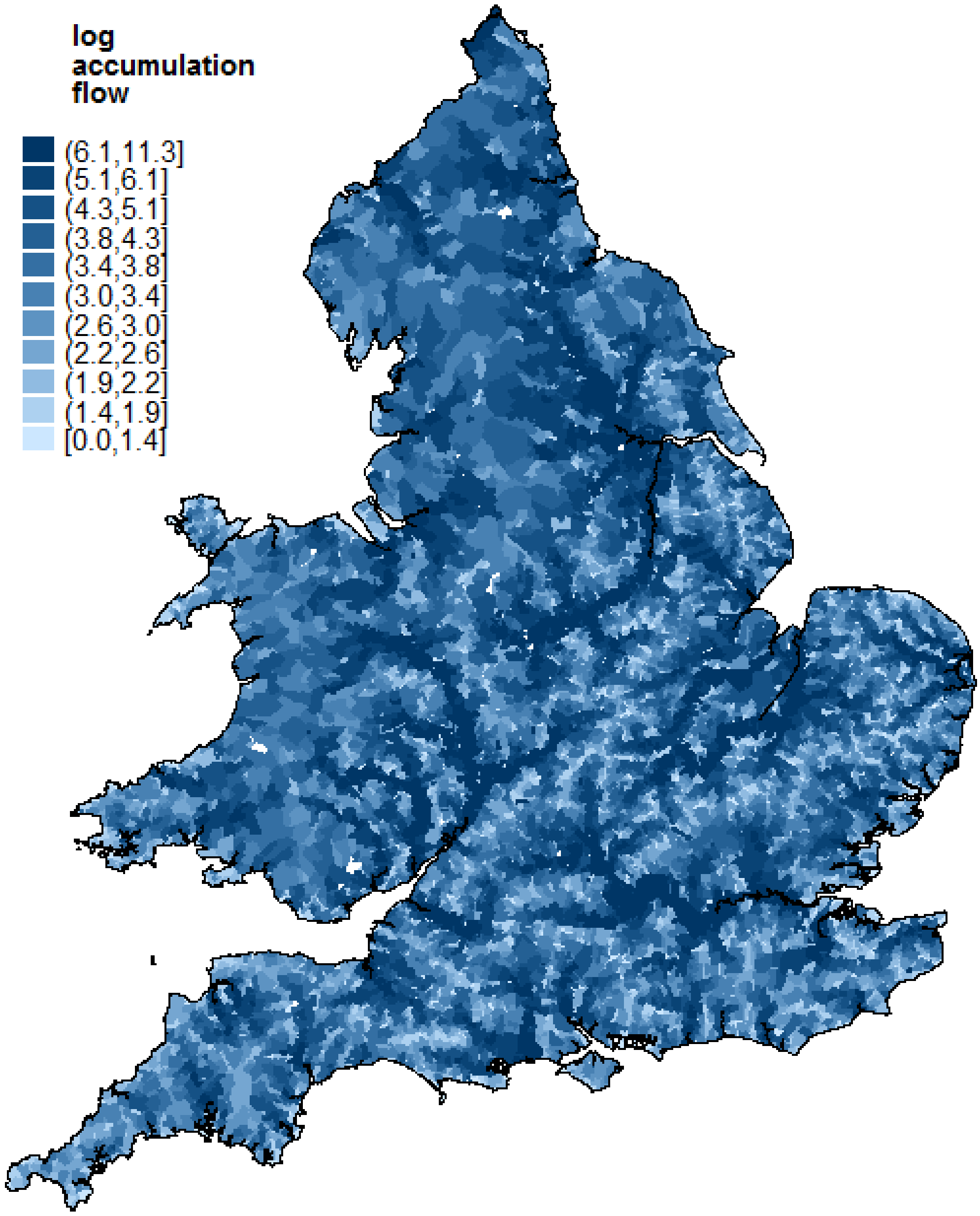


Figure 8. Accumulation flow in England. Source: HydroSHEDS: Lehner, Verdin and Jarvis (2008).

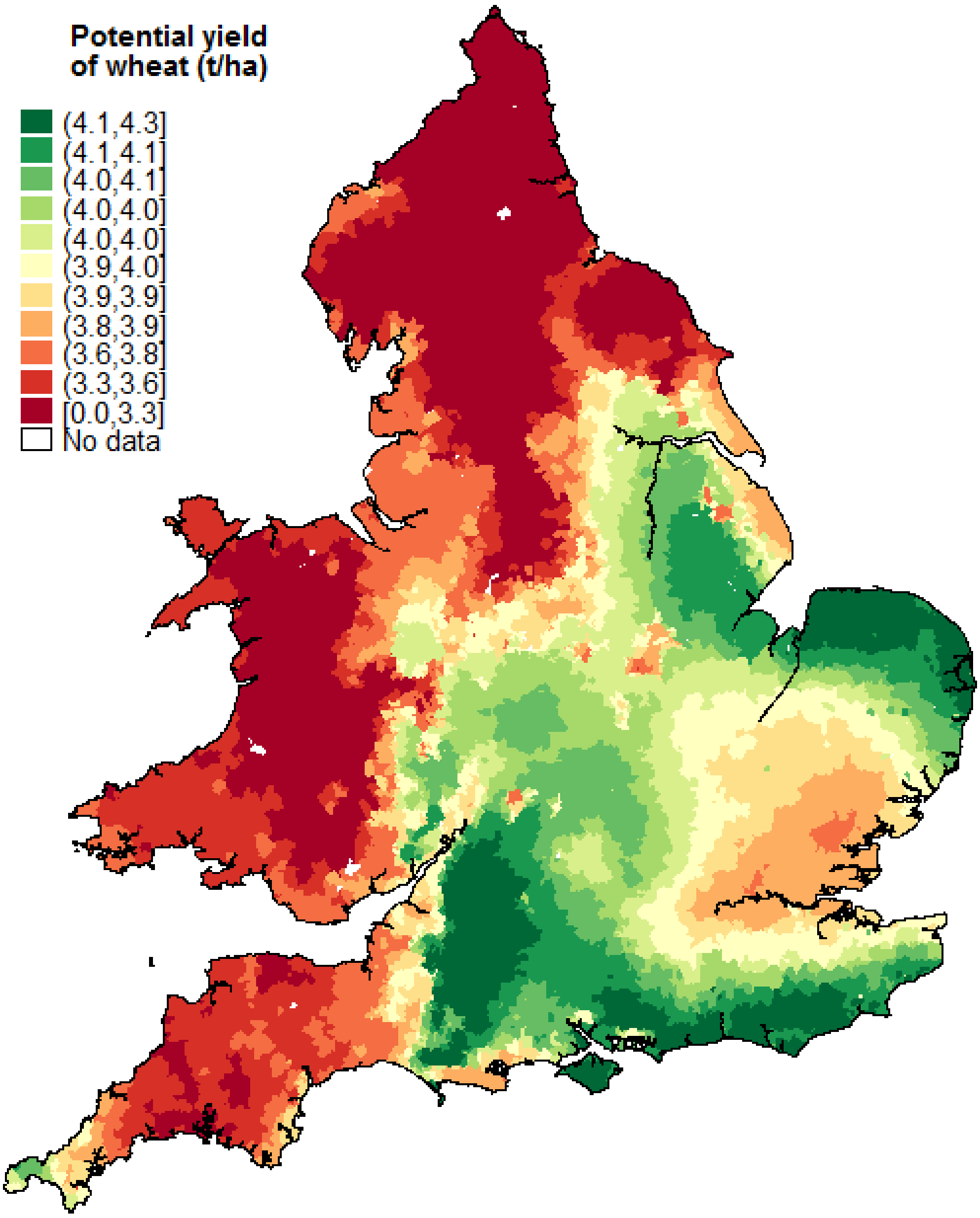


Figure 9. Potential yield attainable for wheat with intermediate level of agricultural inputs and no artificial irrigation (in tonnes per hectare). Source: GAEZ FAO (2015).

Answers to Questions.] THE COMMISSIONERS ON THE POOR LAWS. 67 *a*

QUESTIONS, &c. PART FIRST, Comprising Extracts (A.) (B.) (C.) from Parliamentary Documents, and QUESTIONS 1 to 13.	County of CAMBRIDGE—*continued*. ANSWERS.	
NAME and COUNTY of Parish or Township to which the Answers refer?	HOLY TRINITY (ISLE OF ELY.) (3)	TRUMPINGTON. (2)
SIGNATURE of RESPONDENT?	*Charles Mosely*, *Edward Stevens*, } Overseers.	*George Cuming*, late Assistant Overseer.
(A.)—POPULATION 1801—1811—1821—1831.	(A.)—2,721—2,285—3,438—4,325.	(A.)—494—508—540—722.
(B.)—POOR'S RATES, 1803—1813—1821—1831.	(B.)—£1,719—£2,820—£2,596—2,850.	(B.)—£388—£366—£383—£372.
(C.)—EXPENSE per head on the whole Population i[n] 1803—1813—1821—1831, estimated by th[e] nearest Census.	(C.)—12*s.* 7*d.*—£1. 4. 9.—15*s.* 1*d.*—13*s.* 2*d.*	(C.)—15*s.* 8*d.*—14*s.* 4*d.*—14*s.* 2*d.*—10*s.* 3*d.*
5.—NUMBER of Agricultural Labourers in your Pa[rish]?—	5.—170, besides a considerable number of watermen and porters.	5.—Number above 20, 82; under 20 and above 10, 50 and upwards; total, 132.
6.—NUMBER of Labourers generally out of Employ[ment], and how maintained in Summer and i[n] Winter?—	6.—Summer, average 6; Winter, average 50, maintained by the parish.	6.—Summer, 6 on the parish funds; Winter, 12 ditto.

Figure 10. Sample page from the Poor Law Commission Report for two parishes, Holy Trinity and Trumpington, in Cambridgeshire. We construct winter and summer unemployment by dividing the answers to question 6 by the answer of question 5. We approximate generosity of poor relief with the value of poor's rates in 1803 (first entry of question B) divided by the 1801 population (first entry of question A).

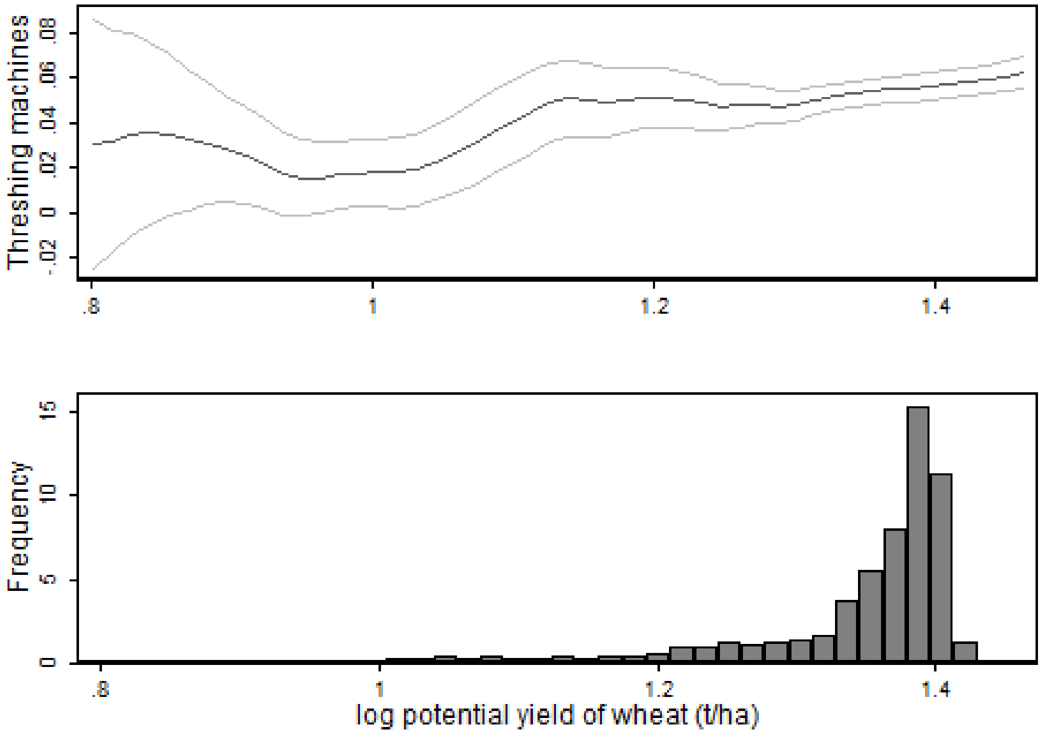


Figure 11. Panel A. Visualization of the First Stage: number of ads and potential yield of wheat.

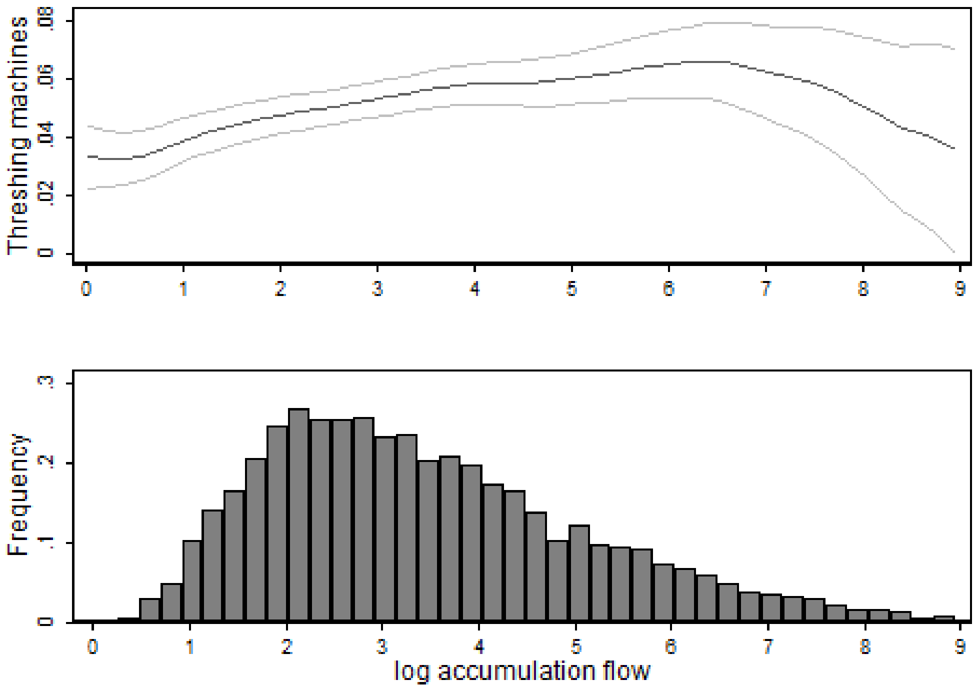


Figure 11. Panel B. Visualization of the First Stage: number of advertisements and accumulation flow.

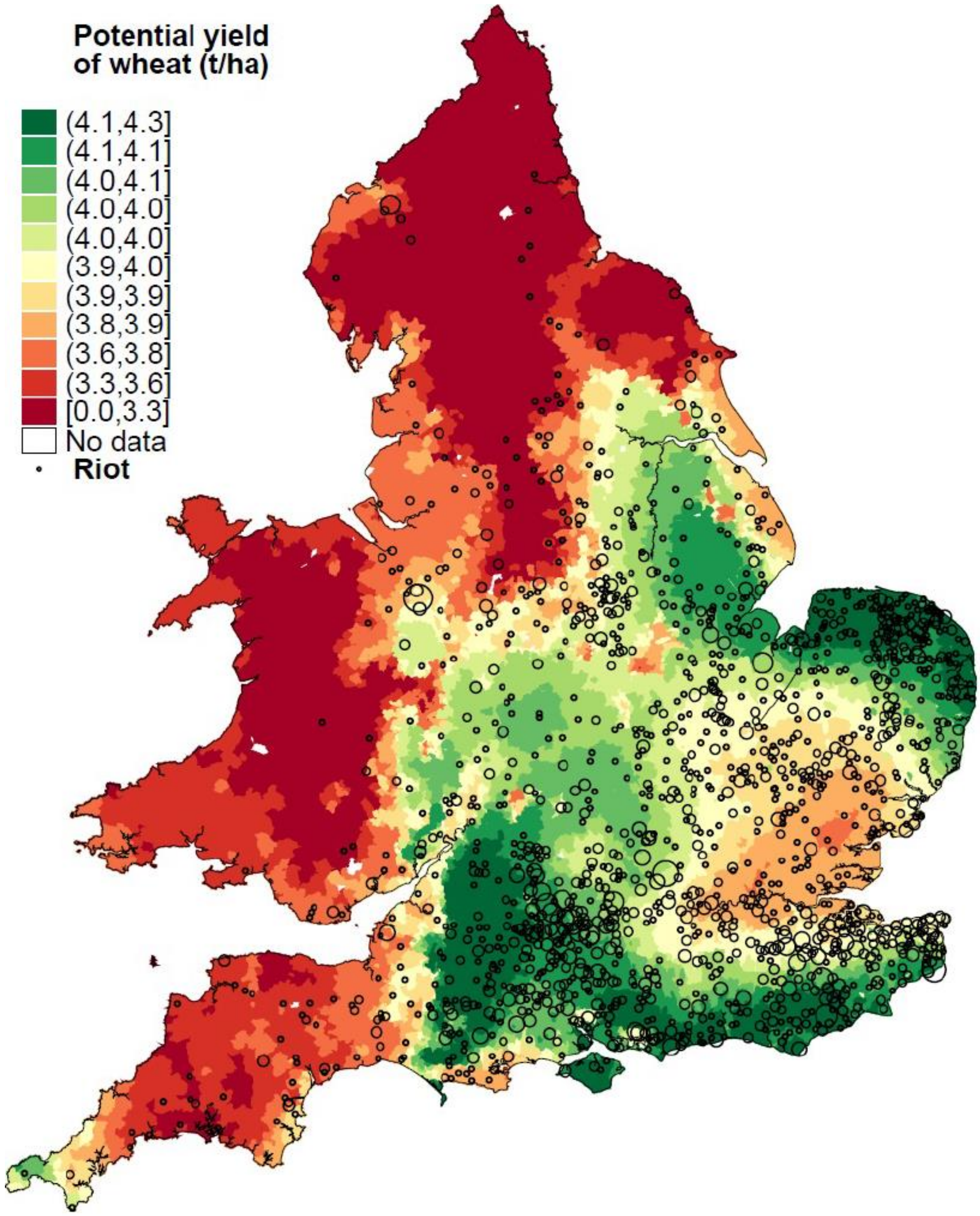


Figure 12. Potential yield attainable for wheat with intermediate level of agricultural inputs and no artificial irrigation and 'Swing' riots. Black circles show the centroid of the parishes in which 'Swing' riots happened: the size of the circle is proportional to the number of episodes recorded in each of these parishes. Sources: GAEZ FAO (2015) and Holland (2005).

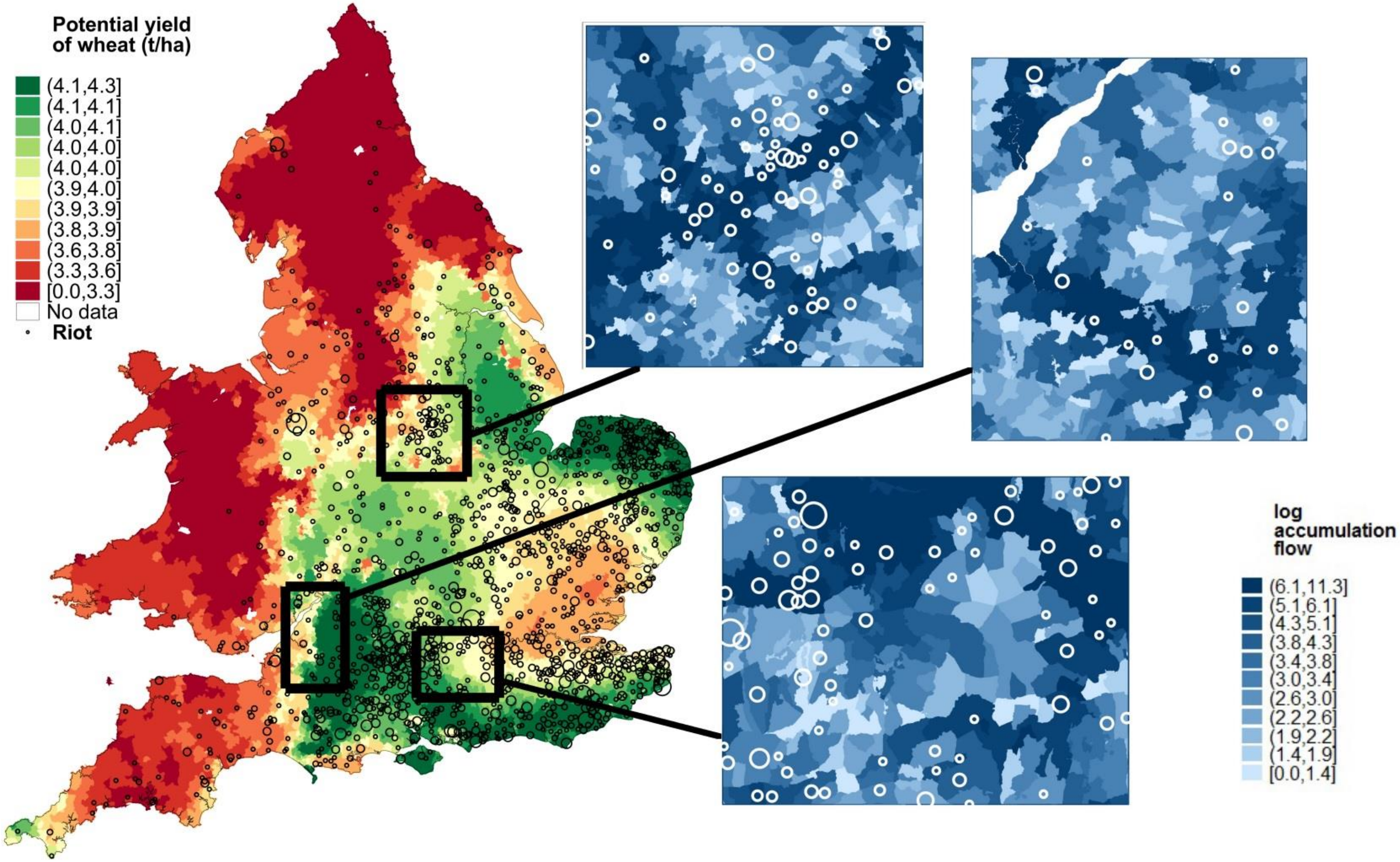


Figure 13. Illustration of Reduced Form. The map on the left reproduces the potential yield of wheat and the location of the Swing riots across England and Wales. The three panels on the right magnify three areas of the map, for which they show the location of the riots (as solid black dots) and the log accumulation flow in the background.

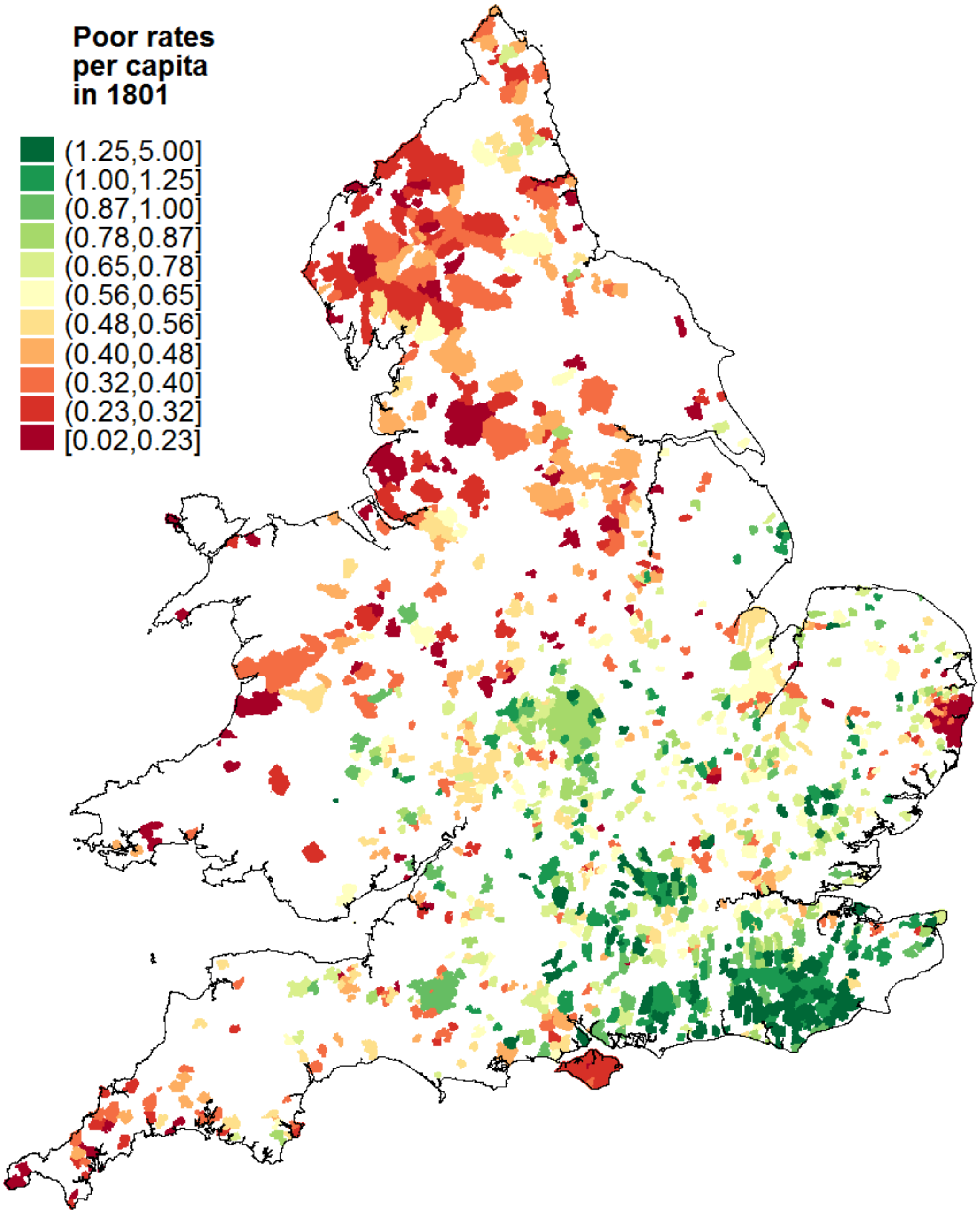


Figure 14. Poor Rates collected in 1803 divided by residents in 1801.

TABLES

Dep. var.:	Winter unemployment – summer unemployment		
Threshing machines	0.021**	0.016*	0.017**
	(0.008)	(0.008)	(0.008)
log(1821 population)		0.013***	0.017***
		(0.003)	(0.006)
log(Parish area)			-0.008
			(0.006)
% families in agriculture			-0.021
			(0.023)
log(sex ratio)			0.001
			(0.038)
log(distance to Elham)			-0.036***
			(0.009)
log(dist. to city with newspaper)			0.014**
			(0.005)
Constant	0.054***	-0.032	0.226***
	(0.004)	(0.021)	(0.061)
Observations	618	618	618
R-squared	0.006	0.026	0.093

Table 1. Threshing machines and the labor market. The dependent variable in columns 1-3 is the winter minus the summer unemployment rate. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Main variables	Average	St. Dev.	Observations
“Threshing machine” advertisements	0.061	0.286	10099
Swing riots	0.301	1.083	10099
Attacks on machines	0.052	0.363	10099
Adoption of threshing and mowing machines after riots	0.054	0.381	10099
Number of patents before riots (1813-1828)	0.103	2.659	10099
Number of patents after riots (1832-1843)	0.153	4.259	10099
Share of land in enclosed commons (until 1820)	2.715	4.055	7019
Unemployment	Average	St. Dev.	Observations
Unemployment share in agriculture during winter	0.137	0.158	673
Unemployment share in agriculture during summer	0.071	0.116	695
Unemployment share in agriculture: winter - summer	0.060	0.108	649
Parish characteristics	Average	St. Dev.	Observations
1821 Population	1165.576	4580.774	10099
Share of families in agriculture in 1821	0.679	0.245	10099
Sex ratio in 1821	1.023	0.204	10099
Geographical characteristics	Average	St. Dev.	Observations
Potential yield of wheat (intermediate inputs) - t/ha	3.805	0.421	10099
log accumulation flow - number of cells	3.488	1.726	10099
Potential yield of grass (low inputs) - t/ha	0.771	0.064	10099
log(Parish area)	16.041	0.933	10099
Relevant distances	Average	St. Dev.	Observations
Distance to closest city with newspaper - Km	24.337	17.978	10099
Distance to Elham (first riot location) - Km	236.304	107.583	10099
Distance to closest industrial city - Km	66.483	38.081	10099
Weather variables	Average	St. Dev.	Observations
Abnormal precipitation in the spring of 1830 - mm	18.679	15.706	10099
Abnormal precipitation in the summer of 1830 - mm	104.109	22.746	10099
Abnormal temperature in the fall of 1830 - degrees	0.277	0.068	10099

Table 2. Summary statistics.

Dep. var.:	Number of Swing riots				
	(1)	(2)	(3)	(4)	(5)
“Threshing machine” Advertisment	0.288***	0.269***	0.217***	0.270***	0.227***
	(0.067)	(0.067)	(0.067)	(0.080)	(0.081)
log(1821 population)	0.190***	0.159***	0.152***	0.184***	0.184***
	(0.013)	(0.017)	(0.017)	(0.018)	(0.018)
log(Parish area)		0.067***	0.078***	0.136***	0.134***
		(0.019)	(0.019)	(0.027)	(0.027)
% families in agriculture		-0.046	-0.092*	-0.143**	-0.157**
		(0.050)	(0.048)	(0.070)	(0.069)
log(sex ratio)		-0.129***	-0.098**	-0.042	-0.005
		(0.046)	(0.046)	(0.060)	(0.061)
log(distance to Elham)		-0.344***	-0.204***	0.266***	0.372***
		(0.033)	(0.045)	(0.070)	(0.072)
log(dist. to city with newspaper)		-0.018	-0.018	-0.014	-0.009
		(0.016)	(0.018)	(0.021)	(0.023)
Abnormal precipitation, spring 1830				-0.009***	-0.011***
				(0.003)	(0.003)
Abnormal precipitation, summer 1830				0.001	0.001
				(0.002)	(0.002)
Abnormal temperature, fall 1830				-2.748***	-1.957**
				(0.777)	(0.873)
Percentage of land enclosed in 1820				0.001	0.000
				(0.004)	(0.004)
Constant	-0.875***	0.149		-3.415***	
	(0.072)	(0.251)		(0.430)	
Region fixed effects (5)			✓		✓
Observations	10,099	10,099	10,099	7,019	7,019
R-squared	0.054	0.092	0.100	0.097	0.103

Table 3. Threshing machines and riots. Column 1 reports estimates of equation (1) when controlling for 1821 population only; column 2 and 4 report estimates of equation (1) and column 3 and 5 report estimates of equation (2) in the text. Columns 4 and 5 include weather variables and enclosures as controls. Dependent variable is the number of ‘Swing’ riots. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Dep. var.:	Share wheat area, 1801	log(1821 population)	Share wheat area, 1801	log(parish area)	log(sex ratio)	Share of agriculutral employment in 1821
log(potential yield wheat) × log(accumulation flow)	0.035	-0.422***	0.035	-0.150	-0.002	0.022*
	(0.022)	(0.117)	(0.022)	(0.130)	(0.006)	(0.012)
log(potential yield wheat)	0.085	0.633	0.085	-0.722	-0.009	-0.030
	(0.088)	(0.456)	(0.088)	(0.524)	(0.022)	(0.043)
log(accumulation flow)	-0.048	0.706***	-0.047	0.179	-0.002	-0.037**
	(0.031)	(0.158)	(0.030)	(0.175)	(0.008)	(0.017)
log(1821 population)			-0.002	0.435***	-0.026***	-0.118***
			(0.002)	(0.011)	(0.002)	(0.002)
Constant	0.262**	4.742***	0.271**	14.410***	0.197***	1.467***
	(0.121)	(0.615)	(0.121)	(0.717)	(0.032)	(0.058)
Observations	3,326	10,099	3,326	10,099	10,099	10,099
R-squared	0.066	0.059	0.066	0.400	0.052	0.357

Table 4. Balancedness table. Dependent variables are reported on the top of each column. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Threshing machine ads			Number of Swing riots					
Equation:	First stage			Reduced form			Two-stages least squares		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
"Threshing machine" ads							5.647***	5.083***	4.813***
							(1.591)	(1.338)	(1.169)
log(pot. yield wheat) × log(accumulation flow)	0.039***	0.041***	0.044***	0.218***	0.193***	0.209***			
	(0.013)	(0.014)	(0.011)	(0.082)	(0.052)	(0.045)			
log(potential yield wheat)	-0.051***	-0.053***	-0.057***	-0.105	-0.242	-0.333**	0.148	-0.057	0.027
	(0.017)	(0.018)	(0.014)	(0.318)	(0.197)	(0.160)	(0.141)	(0.119)	(0.091)
log(accumulation flow)	-0.045	-0.036	-0.070**	-0.294***	-0.252***	-0.272***	-0.009	-0.003	-0.008
	(0.044)	(0.049)	(0.034)	(0.109)	(0.069)	(0.059)	(0.010)	(0.009)	(0.009)
log(1821 population)	0.031***	0.019***	0.015***	0.212***	0.152***	0.142***	0.035	0.064*	0.074**
	(0.003)	(0.004)	(0.004)	(0.014)	(0.017)	(0.017)	(0.050)	(0.034)	(0.029)
log(Parish area)		0.020***	0.026***		0.101***	0.111***		-0.007	-0.019
		(0.005)	(0.005)		(0.021)	(0.021)		(0.041)	(0.042)
% families in agriculture		-0.022	-0.045***		-0.104**	-0.146***		-0.001	0.061
		(0.016)	(0.016)		(0.051)	(0.050)		(0.094)	(0.098)
log(sex ratio)		-0.042***	-0.017		-0.126***	-0.095**		0.085	-0.006
		(0.014)	(0.014)		(0.046)	(0.047)		(0.097)	(0.084)
log(distance to Elham)		-0.005	0.063***		-0.324***	-0.181***		-0.287***	-0.471***
		(0.004)	(0.008)		(0.035)	(0.046)		(0.038)	(0.090)
log(dist. to newspaper)		-0.007	-0.007		-0.009	-0.016		0.027	0.022
		(0.006)	(0.006)		(0.016)	(0.018)		(0.032)	(0.034)
log(potential yield grass)	-0.073	-0.267***	-0.649***		0.137	0.279**		-0.443	-0.238
	(0.059)	(0.092)	(0.084)		(0.117)	(0.139)		(0.284)	(0.289)
Constant	-0.084	-0.228***		-0.839*	-0.078		-0.429	1.137*	
	(0.053)	(0.084)		(0.434)	(0.437)		(0.388)	(0.656)	
Region fixed effects (5)			✓			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099
R-squared	0.019	0.021	0.049	0.061	0.092	0.102			
F-stat excluded instrument	9.5	9.0	17.4						
Rubin-Anderson test (*p*)							0.007	0.000	0.000

Table 5. Identification. Columns 1-3 report estimates of the first stage regression (equation 3). Columns 4-6 report estimates of the reduced form regression (equation 4). Columns 7-9 estimate equations (1) and (2) with two-stages least squares. The dependent variable is the number of advertisements that mention a "threshing machine" in each parish on columns 1-3 and number of Swing riots in the parish in columns 4-9. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of attacks on threshing machines			Other type of revolt		
	(1)	(2)	(3)	(4)	(5)	(6)
				Panel A. OLS estimates		
"Threshing machine" ads	0.083***	0.073**	0.064**	0.156***	0.157***	0.144***
	(0.028)	(0.028)	(0.029)	(0.050)	(0.050)	(0.050)
log(1821 population)	✓	✓	✓	✓	✓	✓
Parish-level characteristics		✓	✓		✓	✓
Region fixed effects (5)			✓			✓
				Panel B. Reduced form estimates		
log(pot. yield wheat) × log(accumulation flow)	0.037**	0.028***	0.030***	0.181***	0.165***	0.179***
	(0.017)	(0.010)	(0.009)	(0.067)	(0.044)	(0.039)
log(pot. yield) & log(acc. flow)	✓	✓	✓	✓	✓	✓
log(1821 population)	✓	✓	✓	✓	✓	✓
Parish-level characteristics		✓	✓		✓	✓
Region fixed effects (5)			✓			✓
				Panel C. Two-stages least squares estimates		
"Threshing machine" ads	0.956***	0.738***	0.692***	4.691***	4.345***	4.121***
	(0.328)	(0.249)	(0.218)	(1.315)	(1.154)	(1.010)
log(pot. yield) & log(acc. flow)	✓	✓	✓	✓	✓	✓
log(1821 population)	✓	✓	✓	✓	✓	✓
Parish-level characteristics		✓	✓		✓	✓
Region fixed effects (5)			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099

Table 6. Type of unrest. Panel A reports OLS estimates of equation (1) and (2); panel B. reports reduced form estimates of equation (4) and panel C reports two-stages least squares estimates of equation (1) and (2). The dependent variable in columns 1-3 the number of attacks on threshing machines; in columns 4-6 the dependent variable is the number of Swing riots that did not involve the attack of a threshing machine. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of Swing riots								
		Closest manufacturing city			Closest manufacturing city			Closest manufacturing city	
Sample of parishes:	All	≥ 62Km	< 62Km	All	≥ 62Km	< 62Km	All	≥ 62Km	< 62Km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A. OLS								
"Threshing machine" ads	0.288***	0.406***	0.120**	0.269***	0.390***	0.091	0.217***	0.312***	0.063
	(0.067)	(0.104)	(0.060)	(0.067)	(0.102)	(0.060)	(0.067)	(0.103)	(0.059)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	10,099	5,049	5,050	10,099	5,049	5,050	10,099	5,049	5,050
R-squared	0.054	0.066	0.046	0.092	0.118	0.074	0.100	0.135	0.077
p-value close = distant		0.017			0.012			0.037	
	Panel B. Reduced form								
log(pot. yield wheat) × log(accumulation flow)	0.218***	0.295***	0.096	0.196***	0.255***	0.112	0.212***	0.268***	0.128*
	(0.082)	(0.095)	(0.075)	(0.052)	(0.056)	(0.072)	(0.045)	(0.047)	(0.073)
log(potential yield wheat)	-0.105	-0.340	0.617**	-0.242	-0.490***	0.365	-0.321**	-0.586***	0.299
	(0.318)	(0.343)	(0.310)	(0.197)	(0.187)	(0.291)	(0.163)	(0.144)	(0.296)
log(accumulation flow)	-0.294***	-0.370***	-0.142	-0.257***	-0.314***	-0.157	-0.277***	-0.330***	-0.179*
	(0.109)	(0.123)	(0.100)	(0.069)	(0.071)	(0.098)	(0.059)	(0.058)	(0.098)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	10,099	5,049	5,050	10,099	5,049	5,050	10,099	5,049	5,050
R-squared	0.061	0.076	0.055	0.092	0.115	0.078	0.102	0.135	0.081
p-value close = distant		0.099			0.118			0.107	

Table 7. Mechanism: Distance to closest manufacturing center. Panel A reports OLS estimates of equation (2) and Panel B reports reduced form estimates of equation (4). The table reports results after splitting the sample according to the distance to the closest manufacturing center. Columns (1), (4) and (7) report coefficients for the regressions that include all parishes; columns (2), (5) and (8) report coefficients for the 5049 parishes below the median parish in terms of distance to the closest manufacturing center and columns (3), (6) and (9) report coefficients for the 5050 parishes above the median parish. The median parish is Winchfield in Hampshire which lies 62 Km from London. Manufacturing centers are Bristol, Blackburn, Bolton-le-Moors, Liverpool, Manchester, Prestwich, Rochdale, Whalley, London, Norwich, Birmingham, Bradford, Halifax, Sheffield and York. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of Swing riots								
Sample of parishes:	All	High enclosures	Low enclosures	All	High enclosures	Low enclosures	All	High enclosures	Low enclosures
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A. OLS								
"Threshing machine" ads	0.328***	0.446***	0.116	0.312***	0.409***	0.105	0.233***	0.326***	0.053
	(0.081)	(0.110)	(0.099)	(0.081)	(0.111)	(0.099)	(0.082)	(0.112)	(0.101)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	7,019	3,468	3,551	7,019	3,468	3,551	7,019	3,468	3,551
R-squared	0.077	0.082	0.075	0.085	0.096	0.083	0.099	0.114	0.091
p-value high = low		0.027			0.041			0.070	
	Panel B. Reduced Form								
log(pot. yield wheat) × log(accumulation flow)	0.669***	0.668***	0.683	0.701***	0.714***	0.710	0.672***	0.663***	0.809*
	(0.186)	(0.194)	(0.453)	(0.186)	(0.193)	(0.449)	(0.180)	(0.187)	(0.453)
log(potential yield wheat)	0.649	0.373	1.651	0.463	-0.244	1.876	0.133	-0.727	1.392
	(0.565)	(0.578)	(1.414)	(0.560)	(0.588)	(1.444)	(0.554)	(0.586)	(1.488)
log(accumulation flow)	-0.925***	-0.929***	-0.937	-0.964***	-0.990***	-0.967	-0.921***	-0.914***	-1.102*
	(0.254)	(0.266)	(0.620)	(0.254)	(0.265)	(0.615)	(0.245)	(0.257)	(0.620)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	7,019	3,468	3,551	7,019	3,468	3,551	7,019	3,468	3,551
R-squared	0.080	0.077	0.084	0.088	0.090	0.094	0.102	0.110	0.102
p-value high = low		0.975			0.994			0.765	

Table 8. Mechanism: Enclosures and unrest. The table reports OLS estimates of equation (1) and (2) for the subsample of 7019 parishes for which we have information on enclosures. Columns 1, 4 and 7 report coefficients for the regressions that include all parishes; columns 2, 5 and 8 report coefficients for the 3505 parishes above the median parish in terms of enclosures and columns 3, 6 and 9 report coefficients for the 3514 parishes above the median parish in terms of enclosures. Median parish had about 8 percent of land enclosed. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of Swing riots								
Sample of parishes:	All	Non-generous	Generous	All	Non-generous	Generous	All	Non-generous	Generous
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A. OLS								
"Threshing machine" ads	0.371*	0.455*	0.172	0.358*	0.407	0.261	0.308	0.389	0.207
	(0.195)	(0.259)	(0.289)	(0.191)	(0.257)	(0.287)	(0.195)	(0.256)	(0.298)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	1,333	667	666	1,333	667	666	1,333	667	666
R-squared	0.061	0.097	0.106	0.153	0.171	0.160	0.156	0.176	0.163
p-value generous = non-generous		0.466			0.706			0.642	
	Panel B. Reduced Form								
log(pot. yield wheat) × log(accumulation flow)	0.253**	0.209***	-0.513	0.221**	0.190***	-0.284	0.278***	0.254***	-0.217
	(0.118)	(0.073)	(0.848)	(0.086)	(0.060)	(0.792)	(0.090)	(0.073)	(0.828)
log(potential yield wheat)	-0.067	-0.342	7.430*	-0.441	-0.589***	5.194	-0.653**	-0.778***	5.305
	(0.380)	(0.219)	(3.985)	(0.293)	(0.223)	(3.738)	(0.305)	(0.245)	(3.939)
log(accumulation flow)	-0.352**	-0.246***	0.692	-0.278***	-0.221***	0.410	-0.348***	-0.294***	0.314
	(0.151)	(0.086)	(1.148)	(0.101)	(0.067)	(1.070)	(0.106)	(0.084)	(1.118)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish characteristics				✓	✓	✓	✓	✓	✓
Region fixed effects (5)							✓	✓	✓
Observations	1,333	667	666	1,333	667	666	1,333	667	666
R-squared	0.074	0.099	0.122	0.151	0.154	0.167	0.156	0.168	0.169
p-value generous = non-generous		0.396			0.550			0.572	

Table 9. Mechanism: Poor Law generosity and unrest. The table reports reduced form estimates of equation (4) for the subsample of 1333 parishes for which we have information from the Poor Law Reports of 1832. Columns (1), (4) and (7) report coefficients for the regressions that include all parishes; columns (2), (5) and (8) report coefficients for the 667 parishes below the median parish in terms of generosity and columns (3), (6) and (9) report coefficients for the 666 parishes above the median parish in terms of generosity. Median parish collects on average £0.6 per person. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Patents 1832-1843				Threshing machines + mowing machines 1835-1853			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance to machine attack (meters)	0.396*	0.304**	0.457**	0.385*	1.047**	1.235**	1.441**	1.674***
	(0.208)	(0.138)	(0.194)	(0.226)	(0.533)	(0.531)	(0.584)	(0.562)
Patents 1813-1829		0.742***	0.710***	0.709***				
		(0.138)	(0.139)	(0.139)				
Threshing machines 1800-1830						0.101***	0.084***	0.072**
						(0.033)	(0.032)	(0.032)
log(1821 population)			0.041***	0.042***			0.029***	0.028***
			(0.009)	(0.009)			(0.007)	(0.008)
log(Parish area)			-0.025**	-0.026**			0.008	0.013
			(0.010)	(0.011)			(0.009)	(0.009)
% families in agriculture			-0.027	-0.026			0.010	-0.004
			(0.017)	(0.017)			(0.027)	(0.027)
log(sex ratio)			0.021	0.016			-0.023	-0.019
			(0.014)	(0.013)			(0.026)	(0.026)
log(distance to Elham)			-0.001	-0.003			-0.011*	0.009
			(0.005)	(0.006)			(0.007)	(0.007)
log(dist. to newspaper)			-0.028**	-0.029**			-0.038**	-0.040***
			(0.012)	(0.012)			(0.016)	(0.015)
Constant	0.027***	0.007	0.256**		0.046***	0.036***	-0.113	
	(0.006)	(0.006)	(0.130)		(0.008)	(0.008)	(0.117)	
Region fixed effects (5)				✓				✓
Observations	9,665	9,665	9,665	9,665	6,703	6,703	6,703	6,703
R-squared	0.001	0.377	0.388	0.388	0.001	0.006	0.017	0.027

Table 10. Aftermath: Effect of riots on innovative activity. In columns 1-4 the dependent variable is the number of patents registered by inventors in the years 1833-43. In columns 5-8 the dependent variable is the number of threshing machines and mowing machines found on newspaper advertisements in the years 1835-1853. See text for details and appendix for variable construction. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A Data Appendix

A.1 Ancient parishes of England and Wales

To construct our database, we start from the map of ancient parishes of England and Wales prepared by Burton, Southall, Westwood and Carter (2004). This map derives from earlier electronic maps by Kain and Oliver (2001), and contains a GIS database for all parishes of England and Wales in 1851. To our knowledge, this is the earliest date for which such a map exists. The map consists of 22,729 separate polygons, each identifying a separate place in England and Wales. These places are localities smaller than a parish, so that a given parish is often made of several distinct places. Because we observe all our variables at the parish level, we start by aggregating the 22,729 polygons into 11,285 parishes.[45]

Next, we aggregate a subset of these parishes into larger units of observation. We do this in two cases. First, large urban areas such as London, Liverpool or Manchester consists of several distinct parishes. Treating these areas as separate observations is incorrect, because we always observe riots and threshing machines for a whole city, and we are never able to assign them to any specific area within the city. Thus, we assign all parishes belonging to a city to a single observation: panel A of table A1 reports the full list of cities along with the number of parishes aggregated.[46]

We also aggregate different parishes into larger units when the information from at least one of our sources does not allow us to compute one of our variables more precisely. This happens when one of our sources records a riot, a threshing machine or Census population for a large area comprising several parishes. In these cases, we also aggregate all variables at the level of the larger unit of observation. Panel B of table A2 report the full list of observations that we obtain by aggregating multiple parishes in this way.

At the end of this process, we are left with 10,700 separate observations. Of these, we are able to match 10,123 to the 1821 Population Census based on the county and parish name. We drop 21 of these observations because they have 0 population in 1821: this leaves us with the sample of 10,102 observations. Finally, 3 of these parishes have 0 potential yield of wheat according to the FAO database: when we take the logarithm of this variable we drop them and we are left with our final database of 10,099 observations.

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[45] We do this based on the fields *GAZ_CNTY* and *PAR*, which identify the county and the parish in the map. We drop

[46] There is a second reason for aggregating parishes within cities. Because most of riots and almost all machines appear in rural areas, keeping separate observations for each urban parish effectively duplicates observations with no riots and no machines. This would introduce the "Moulton problem" (Moulton, 1990) and, by biasing standard errors downwards, it would artificially increase the precision of our estimates.

County	City	Parishes aggregated	County	City	Parishes aggregated
London	London	80	Huntingdonshire	Sawtry	3
Yorkshire, west riding	York	55	Nottinghamshire	Nottingham	3
Norfolk	Norwich	36	Kent	Dover	3
Devon	Exeter	25	Worcestershire	Droitwich	3
Kent	Canterbury	24	Dorset	Wareham	3
Lincolnshire	Lincoln	21	Lincolnshire	Saltfleetby	3
Gloucestershire	Bristol	20	Suffolk	Fornham	3
Oxfordshire	Oxford	13	Kent	Rochester	3
Cheshire	Chester	13	Dorset	Shaftesbury	3
Suffolk	Ipswich	13	Essex	Maldon	3
Hampshire	Winchester	12	Somerset	Bath	3
Gloucestershire	Gloucester	12	Glamorganshire	Cardiff	3
Essex	Colchester	12	Hertfordshire	Hertford	3
Cambridgeshire	Cambridge	12	Lincolnshire	Wainfleet	3
Leicestershire	Leicester	11	Suffolk	Bury st edmunds	2
Worcestershire	Worcester	11	Pembrokeshire	Pembroke	2
Sussex	Chichester	11	Yorkshire, west riding	Ferry fryston	2
Sussex	Hastings	7	Wiltshire	Marlborough	2
Shropshire	Shrewsbury	7	Suffolk	Bungay	2
Hampshire	Southampton	7	Herefordshire	Sutton	2
Sussex	Lewes	6	Devon	Dartmouth	2
Herefordshire	Hereford	6	Norfolk	Walpole	2
Lincolnshire	Stamford	5	Northamptonshire	Peterborough	2
Surrey	Guildford	5	Norfolk	Thetford	2
Bedfordshire	Bedford	5	Warwickshire	Warwick	2
Northamptonshire	Northampton	5	Glamorganshire	Swansea	2
Berkshire	Wallingford	5	Dorset	Dorchester	2
Huntingdonshire	Huntingdon	4	Devon	Plympton	2
Kent	Sandwich	4	Wiltshire	Orcheston	2
Suffolk	Sudbury	4	Nottinghamshire	Sutton bonington	2
Cambridgeshire	Ely	4	Buckinghamshire	Stony stratford	2
Wiltshire	Salisbury	4	Devon	Plymouth	2
Yorkshire, north riding	Thornton dale and ellerburn	4	Norfolk	Warham	2
Brecknockshire	Brecon	4	Cornwall	Launceston	2
Derbyshire	Derby	4	Warwickshire	Coventry	2

Table A1. Panel A. List of cities created by aggregating more than one parish from the original shapefile created by Burton, Southall, Westwood and Carter (2004).

County	City	Parishes aggregated	County	City	Parishes aggregated	County	City	Parishes aggregated
Norfolk	Wiggenhall St German	4	Somerset	Pilton And North Wootton	2	Norfolk	Witchingham	2
Yorkshire, East Riding	Beverley	4	Norfolk	Oxwick And Pattesley	2	Norfolk	Alpington & Yelverton	2
Norfolk	Lynn	4	Herefordshire	Tedstone	2	Wiltshire	Collingbourne	2
Middlesex	Westminster	4	Lincolnshire	Ludford	2	Norfolk	Beckham	2
Berkshire	Windsor	3	Norfolk	Beechamwell	2	Northamptonshire	Boddington	2
Buckinghamshire	Brickhill	3	Wiltshire	Savernake	2	Norfolk	Poringland	2
Norfolk	Bircham	3	Yorkshire, East Riding	Hull	2	Suffolk	Whelnetham	2
Dorset	Blandford	3	Suffolk	Hargrave And Southwell Park	2	Cornwall	St Columb	2
Berkshire	Reading	3	Yorkshire, West Riding	Sawley And Tosside	2	Somerset	Taunton	2
Norfolk	Wretham	2	Worcestershire	Evesham	2	Worcestershire	Pershore	2
Norfolk	Bawburgh And Bowthorpe	2	Nottinghamshire	Retford	2	Kent	Snodland And Paddlesworth	2
Worcestershire	Great Witley & Martley	2	Norfolk	Forncett	2	Lincolnshire	Mumby	2
Middlesex	S.Andrew Holborn & S.George Martyr	2	Norfolk	Glandford And Bayfield	2	Devon	Axminster & Uplyme	2
Norfolk	Ranworth With Panxworth	2	Dorset	Lytchett	2	Wiltshire	Cricklade	2
Norfolk	Terrington	2	Norfolk	Lamas And Little Hautbois	2	Wiltshire	Codford	2
Wiltshire	Tisbury	2	Cumberland	Carlisle	2	Suffolk	Newmarket	2
Suffolk	Icklingham	2	Norfolk	Rudham	2	Norfolk	Upton And Fishley	2
Norfolk	South Walsham	2	Norfolk	Somerton	2	Cambridgeshire	Wisbech	2
Wiltshire	Manningford	2	Norfolk	Sporle And Palgrave	2	Lincolnshire	Somercotes	2
Wiltshire	Lavington	2	Lincolnshire	Great Limber And Brocklesby	2	Kent	Deptford	2
Lincolnshire	Stoke	2	Norfolk	Weasenham	2	Hampshire	Alresford	2
Wiltshire	Cheverell	2	Norfolk	Walton	2	Somerset	Brewham	2
Carmarthenshire	Carmarthen	2	Cambridgeshire	Abington	2	Wiltshire	Chitterne	2
Sussex	Bersted And Pagham	2	Northamptonshire	Cranford	2	Berkshire	Bucklebury Stanford	2
Cornwall	Perranuthnoe And St Hilary	2	Oxfordshire	Barton	2	Kent	Romney	2
Wiltshire	Sherston	2	Leicestershire	Leicester Forest	2	Cornwall	Landrake & St Erney	2
Lincolnshire	Sleaford	2	Norfolk	Long Stratton	2	Dorset	Lulworth	2
Dorset	Whitchurch And Catherson	2	Gloucestershire	Forest Of Dean	2	Berkshire	Abingdon	2
Norfolk	Beeston And Bittering	2	Middlesex	S.Giles in the Fields & S.George Bloomsbury	2	Kent	Barming	2

Table A1. Panel B. List of other geographical units created by aggregating more than one parish from the original shapefile created by Burton, Southall, Westwood and Carter (2004).

A.2 Variable construction

In this section**,** we describe data sources and variable construction.

Threshing machines 1800-1830. We assemble a list of threshing machines in use before the riots from two data sources. The first is built from threshing machines advertisements found on English and Welsh newspapers. The second are the reports of threshing machines on the General Views of Agriculture. We collect newspaper advertisements from the website "British Newspaper Archive:"[48] within the universe of the 60 regional newspaper published between 1800 and 1830, we search for the exact string "threshing machine". We restrict our search to articles classified as either "advertisement" or "classifieds." Next, we read in full each article retrieved, and determine whether it is relevant for our research. We consider relevant information any article that advertises the sale or the lease of a threshing machine or of a farm that lists a threshing machine among its assets. In one case, we also consider the information provided by a threshing machine manufacturer who lists name and location of their clients: these clients are farmers located in parishes all over the country (see Figure 5). We drop all advertisements of threshing machines producers that only provide information about the location of the factory, usually an industrial town. We also only consider a single threshing machine whenever we find the same advertisement printed more than once. In the last step, we manually geo-locate each advertisement, and find the parish in which the threshing machine or the farm is located on the map prepared by Burton, *et al.* (2004). We complement this source with a list of threshing machines we found on the General Views of Agriculture for all English counties. In the second editions of each of these publications, the surveyors devoted an entire chapter to threshing machines, relating information on every machine they found in the countryside, including the name of the owner and the place of operation. We locate each of these machines on the map of Burton *et al.* (2004) and make sure that we do not double count any machine from the newspapers by comparing the names of the owners in the two sources. Whenever we link a parish to either an advertisement or a machine from the General Views, we add 1 to the number of threshing machines we find in that parish.

Swing riots. Data on Swing riot comes from a database compiled by the Family and Community Historical Research Society (Holland 2005). The data contains a comprehensive list of Captain Swing incidents between January 1830 and December 1832. The information comes from official records and historical newspapers and contains the exact date, the parish, and the type of crime perpetrated by rioters. We consider only episodes that happened between August 1830 and December 1832. For each of these episodes, we manually match the parish of the riot to the historical map of English and Welsh parishes (Burton, Southall,

[48] See: http://www.britishnewspaperarchive.co.uk/. We collected these articles during the Spring of 2016.

Westwood and Carter, 2004). On this map, we identify the location of these riots with the county (variable GAZ_CNTY) and either the name of the parish (variable PAR) or the name of the place (variable PLA). In our baseline results, we use a variable that contains every episode listed in the database, irrespective of the nature of the protest.

Attacks on threshing machines. These episodes are a subset of all the riots: they consist of every episode classified as "machine breaking (threshing machine)" in the original database.

1821 Population. Total number of people in a parish comes from the 1821 Census of England (Southall *et al.* 2004). The original variable in the database is TOT_POP: "Total number of inhabitants" in 1821. Data come at the parish level: we merge it manually to the historical map of English and Welsh parishes using the county (variable ANC_CNTY) and parish (variable ANC_PAR) reported in the Census. We use the natural logarithm of this variable in all regressions.

Share of families in agriculture in 1821. We construct this variable with data from the 1821 Census of England (Southall *et al.* 2004) as the number of families chiefly employed in agriculture (variable FAMAGRI) divided by the total number of families in the parish. The total number of families is the sum of three variables: FAMAGRI, FAMTRADE (families chiefly employed in trade) and FAMOTHER (families chiefly employed in other activities). Census data come at the parish level and we merge it to the historical map of English and Welsh parishes as we did with the 1821 population.

Sex ratio in 1821. We compute the sex ratio with data from the 1821 Census as the total number of men (variable TOT_MALE) divided by the total number of women (variable TOT_FEM). Census data come at the parish level and we merge it to the historical map of English and Welsh parishes as we did with the 1821 population. We use the natural logarithm of this variable in all regressions.

Parish area. The total area of the parish (in square kilometers) is calculated with ArcGIS based on the map of historical parishes of England and Wales we produced after aggregating using the map of Burton, Southall, Westwood and Carter (2004). We use the natural logarithm of this variable in all regressions.

Distance to Elham, location of the first Swing riot. We construct this variable as the distance of the centroid of every parish in our map to Elham, the parish that saw the first episode of the Swing riots according to Griffin (2012). We use the natural logarithm of this variable in all regressions.

Distance to closest city with a newspaper. To construct this variable, we first determine which of the newspapers stored on the “British Newspaper Archive” was in print between 1800 and 1830. Next, we manually geo-code the city in which these newspapers were printed. We then calculate the distance of the centroid of every parish in our map to each of the cities that print at least one newspaper. Finally, we keep only the distance to the closest city. We use the natural logarithm of this variable in all regressions.

Abnormal precipitation in the spring (summer) of 1830. We source historical precipitation from Pauling *et al.* (2006). They used documentary evidence and natural proxies to prepare a database with seasonal precipitation for the period 1500-1900 over a 0.5 × 0.5 degrees grid covering Europe (approximately 55.5 × 55.5 kilometers). To construct abnormal precipitation in the spring (summer) of 1830 across England and Wales, we take average spring (summer) precipitation in 1830 and subtract the average spring (summer) precipitation in the years 1800-1828. We do this for every cell that covers the British Isle, obtaining a new raster with the abnormal precipitation in the spring (summer) of 1830. Next, we resample this raster on a finer grid of 88.8 × 88.8 meters with the "nearest" method, and we superimpose it to our historical map of English and Welsh parishes described above. For every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we calculate the average abnormal precipitation in the spring (summer) of 1830 of every cell that falls inside the parish.

Abnormal temperature in the fall 1830. We source historical temperature from Luterbacher *et al.* (2004). They used documentary evidence and natural proxies to prepare a database with seasonal temperature for the period 1500-1900 over a 0.5 × 0.5 degrees grid covering Europe (approximately 55.5 × 55.5 kilometers). To construct abnormal temperature in the fall of 1830 across England and Wales, we follow the same procedure described for abnormal precipitation. We take average fall temperature in 1830 and subtract the average fall temperature in the years 1800-1828. We do this for every cell that covers the British Isle, obtaining a new raster with the abnormal fall temperature of 1830. Next, we resample this raster on a finer grid of 88.8 × 88.8 meters with the "nearest" method, and we superimpose it to our historical map of English and Welsh parishes described above. For every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we calculate the average abnormal temperature in the fall of 1830 of every cell that falls inside the parish.

Share of land enclosed. We source data on enclosures from Gonner (1912). In the tables on pages 270-278, Gonner reports information on the percentage of land in commons that was enclosed before 1870. He collected information across 340 ‘registration districts’ covering 7,019 parishes and 68 percent of England’s area. In order to estimate the percentage of land enclosed *before* the Swing riots, we combine the information on this table with information from the table on page 279-281 of the same book. In this second table, Gonner reports the share of land in commons enclosed in each decade between 1760 and 1870 for every county in England and Wales. We estimate the share of land enclosed in 1820 by multiplying district-level enclosures in 1870 with the proportion of enclosures that happened before 1820 in the county of every district. We use the registration district reported in the 1821 Census to match each parish to its registration district. The parishes in the registration districts of Biggleswade (Bedford), Billericay, Colchester, Ongar, Romford (Essex) and Market Harborough (Leicester) have the median level of enclosure: we define parishes with ‘high’ enclosures those parishes with more than this level of enclosures.

Potential yield of wheat with intermediate (low) inputs. We construct potential yield of wheat for each parish by combining data from the Food and Agriculture Organization Global Agro-Ecological Zones database (FAO-GAEZ) and the map of English and Welsh parishes. We use the potential yield for summer wheat computed under the assumption of intermediate (low) inputs and rain-fed irrigation. The original data is a raster that covers the entire land mass of the Earth on a grid of about 9.25 × 9.25 kilometers. We first resample the raster on a finer grid of 88.8 × 88.8 meters with the "nearest" method. Next, we superimpose the raster to our historical map of English and Welsh parishes described above, and for every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we take the average potential yield of all the cells that fall inside the parish. We use the natural logarithm of these variables in all regressions.

Potential yield of grass with low inputs. We construct potential yield of grass for each parish by combining data from the Food and Agriculture Organization Global Agro-Ecological Zones database (FAO-GAEZ) and the map of English and Welsh parishes. We use the potential yield for grass computed under the assumption of low inputs and rain-fed irrigation. We calculate the average potential yield of grass with the same procedure detailed above for the potential yield of wheat. We use the natural logarithm of this variable in all regressions.

Accumulation flow. We source the *accumulation flow* from the HydroSHEDS database, prepared by Lehner, Verdin and Jarvis (2008). They used elevation data from the Shuttle Radar Topography Mission at the 3 arc-second resolution to derive a accumulation flow on a global, 15 arc-seconds grid (approximately 462.5 × 462.5 meters). The accumulation flow captures the amount of upstream area that drains into each cell of this grid, and it is calculated by counting the number of upstream cells that drain water into a target cell. To assign the average accumulation flow to each parish in England, we first resample the raster on a finer grid of 88.8 × 88.8 meters with the "nearest" method. Next, we superimpose the raster to our historical map of English and Welsh parishes described above, and for every cell of the raster we take its centroid and assign it to the parish where the centroid falls. For every parish we take the average accumulation flow of all the cells that fall inside the parish. We use the natural logarithm of this variable in all regressions and resample the raster on a finer grid of 88.8 × 88.8 meters with the "nearest" method. Next, we superimpose the raster to our historical map of English and Welsh parishes described above, and for every cell of the raster we take its centroid and assign it to the parish where the centroid falls. Finally, for every parish we take the average potential yield of all the cells that fall inside the parish.

Relative unemployment in 1834. We collect data on winter and summer unemployment from the Appendix B.1 of the "Poor Law Report" of 1834.[49] The report is a Parliamentary inquiry that collects information on a selected sample of parishes across England and Wales. Figure 10 shows the questionnaire and the answers provided by two parishes. Officials surveyed a total of 1,391 parishes, and recorded the answers provided by local informants. Not all of these places provided valid answers to every question and we have valid unemployment data for 618 parishes. To reconstruct parish-level unemployment, we digitize the answers of question 5 and 6.[50] Question 5 reads: 'number of agricultural labourers in your parish?'; question 6 reads: 'number of labourers generally out of employment, and how maintained in summer and in winter?'. We construct unemployment as number of labourers out of employment divided by the total number of labourers: we do this separately for winter and for summer and we set to missing 6 parishes where unemployment is above 100 percent. We construct relative unemployment as the difference between winter and summer unemployment.

Poor law generosity. We define generosity of a parish based on data from the "Poor Law Report" of 1834. From the report, we digitized the population in 1801 (first entry of question A on the questionnaire) and *Poor Rates* collected in 1803 (first entry of question B on the questionnaire). We define the generosity of a parish as total value of poor rates in 1803 divided by the 1801 population in the parish. The median parish in terms of generosity is Doddington in Cambridgeshire, which collects 0.6 pounds per capita; we define as "generous" every parish that provides support above this level.

Distance to closest manufacturing city. We consider 15 manufacturing centers in 1821: Bristol in Gloucestershire, Blackburn, Bolton-le-Moors, Liverpool, Manchester, Prestwich, Rochdale, Whalley in Lancashire, London, Norwich in Norfolk, Birmingham in Warwickshire and four cities in Yorkshire, West Riding: Bradford, Halifax, Sheffield and York. We identify these cities by selecting every parish which in 1821 counted more than 45'000 inhabitants. This yielded a list of 25 parishes, from which we excluded 10 parishes that are today part of

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[49] Full title: *Report from his Majesty's commissioners for inquiring into the administration and practical operation of the Poor Laws.*

[50] Officials were sent to survey parishes in 3 different waves between 1833 and 1834, and the questionnaire they asked varied slightly between these waves. Question 5 and 6 in the first two issues became question 6 and 7 in the 3rd issue. The content of the answers did not change.

Greater London.[52] In the 1821 census, these centers had on average 82 percent of the families employed in trade and less than 5 percent employed in agriculture. In the rest of English parishes, 21 percent of families were chiefly employed in trade and 68 percent in agriculture. We use the coordinates of the centroid of these cities and of every parish in England to construct the distance of every parish to the closest of manufacturing center. We then divide the sample into two groups: above and below the median distance to these cities. The median parish in terms of distance to manufacturing cities is Winchfield in Hampshire which lies 62 Km from London.

Agricultural machines: 1832-1853. We collect information on agricultural machine in use in the 20 years following the riots from the British Newspaper Archive. We first select 7 years after the riots: 1835, 1838, 1841, 1844, 1847, 1850 and 1853. Next, we searched in all newspapers published in these years farm advertisements that mention either "threshing machines," or "mowing machines." We read each of these advertisements in full, determining whether they are relevant for our research, and then locating on the map of Burton *et al.* (2004). The measure of agricultural machine diffusion is the sum of the threshing machine and mowing machine we found in each parish.

Patents: 1813-1843. We digitize every patent registered in England between the 20th of November 1813 and the 15th of June 1843 from Woodcroft (1854). This publication reports, for every patent that was registered in England, the title, the date of registration, the name and occupation of the inventor(s) and the place where they lived. We digitize each of this information and located the parish in which each of these inventors were living at the time of the registration. Whenever more than one inventor claims one patent, we assign to each of the parishes of these inventors a value equal to one divided by the numbers of inventors. We divide patens into two groups: those registered before the 31st of December 1829 (before the riots) and those registered between the 1st of January 1833 and the 15th of June 1843 (after the riots). We do not consider the patents registered during the years 1830-32 to avoid confounding the direct effect of riots on patenting activity.

[52] These are: Westminster, St Leonard Shoreditch, St George Hanover Square, St Matthew Bethnal, St George in the East, St Dunstan Stepney, St Giles in the Fields and St George Bloomsbury, Lambeth, St Pancras, St Marylebone. Considering these places as "manufacturing centers" changes nothing, as they lie close to London.

B Productivity of Threshing Machines

In this section, we attempt to quantify the productivity gains of threshing machines relative to manual labor. Contemporary observers recognized quickly the productivity gains offered by threshing machines (Donaldson, 1794, p. 20; Batchelor, 1813, p.210).[53] However, there exists no systematic analysis of productivity for the machines in use in 1800, nor are we aware of any attempt to determine the productivity of machines operated with different power sources.

We source information on machine productivity from the county surveys of the "General View of Agriculture". These documents contain detailed information on every aspect of agriculture in each of the counties of the United Kingdom. Sir John Sinclair commissioned the General Views as president of the Board of Agriculture in the 1790s, and professional agronomists prepared these documents under the supervision of Arthur Young. Separate volumes cover each county and the commission surveyed most counties twice: once in 1790s and a second time in the 1810s. We collect all editions covering English counties: a total of 38 separate volumes.

All of the General Views published in the 1810s, and several of those that appeared in the 1790s contain a chapter on threshing machines. We read these chapters in full, and collect all information that is useful to determine the productivity of these machines. The officials who prepared these chapters toured the English countryside and took detailed notes of every threshing machine they found. A typical entry in this chapter lists owner and location of the machine, as well as material and shape of each different component. It also reports the mode of operation, the number of men, women and children required to move it and the average quantity of wheat that the machine could thresh in a given amount of time.

We find 121 separate machines in the General Views. To calculate productivity we require information on wheat threshed per unit of time, number of people needed to operate the machine and the main source of power for the machine. Under these constraints, we are able to calculate productivity for 24 horse-powered machines, 3 water-powered machines and a single machine operated by hand. We show the productivities on Figure B1, where we contrast them with the average productivity of a worker threshing with a flail, as estimated by Clark (1987). Our data is too sparse to provide precise measures of relative productivity. However, the differences are stark, and they suggest that horse-powered threshing machines may have been 5 times more productive than manual threshing, and water-powered threshing machines more than 10 times more productive. The estimates also suggest that threshing

[53] In the 1794 General View of Banffshire, Donaldson notes: "Threshing-mills have also been introduced of late, and the advantages of them seem to be so well known and established, that there is no doubt of their soon coming into general use" (Donaldson, 1794, p. 20).

machines operated with human force did not save as much as other types of machines, and did not offer large labor savings. Available information also suggest that water-power threshing machines were significantly more productive than horse-powered, possibly by a factor of two.

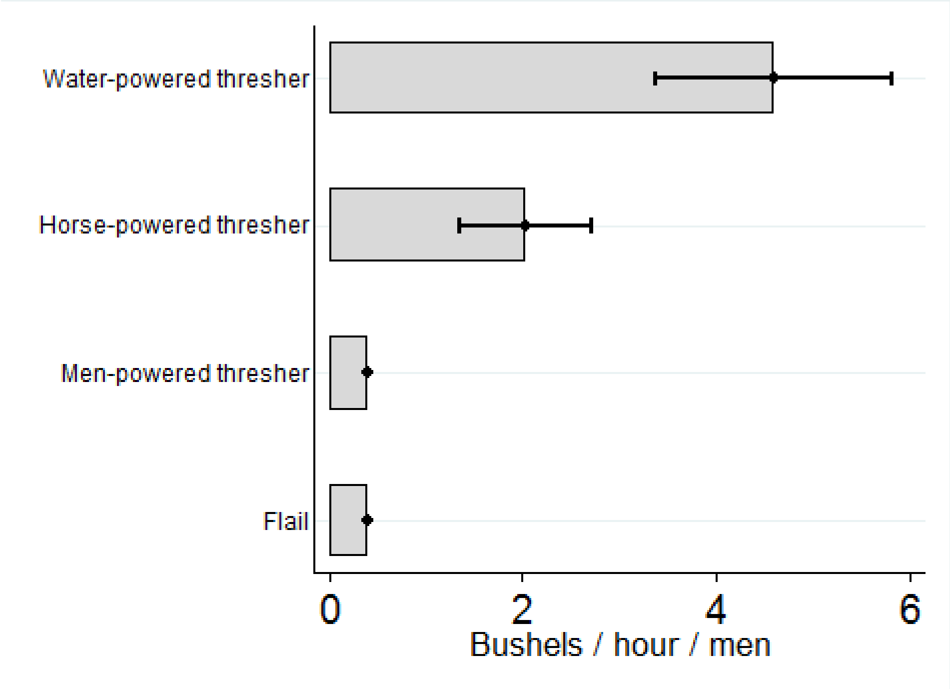


Figure B1. Threshing machine productivity relative to manual threshing. Data for threshing machine comes from the county surveys of the General View of Agriculture. Sample size is 3 water-powered threshing machines, 24 horse-powered threshing machines and 1 men-powered threshing machine. We only consider wheat threshed and convert every quantity in bushels. We assume a 8-hours day of work when the surveys report average grains threshed per day. When farmers used women or children to operate these machines we assume that both women and children cost half of what a man does. This is likely to bias productivity downwards, as figures from the Poor Law Report suggest that on average a woman (child) was paid 37.5% (25%) of what men were paid. Average productivity of manual threshers comes from Clark (1987) who uses primary sources to estimate average productivity of English threshers in 1800s.

C Additional Results

C.1 Historical Weather in England and Wales

FAO researchers compute potential yield for wheat and grass based on soil characteristics, weather records and an agronomic model that assumes the use of a specific input mix. One possible concern with this measure has to do with the weather data used for these calculations. This is because FAO researchers use average weather conditions for the period 1961-1990, which may be different from weather conditions that affected potential yield of wheat at the beginning of 1800.

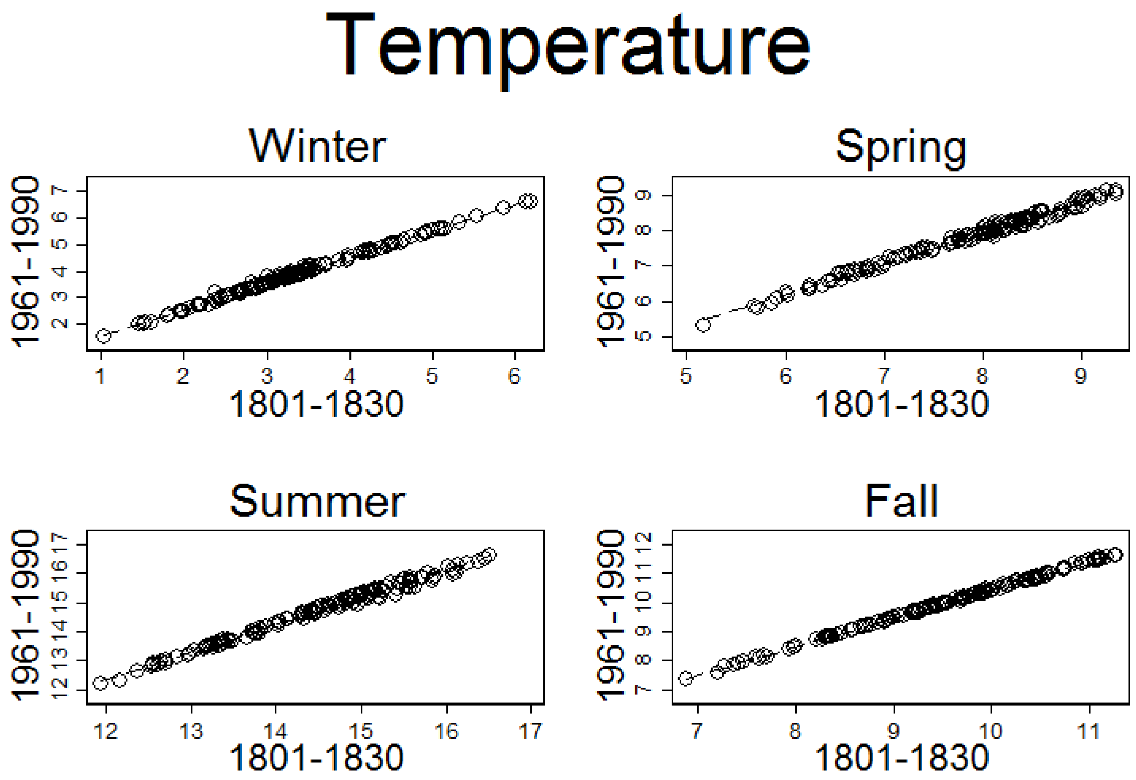
To determine how much weather changed over the last 200 years we perform two separate tests. In the first one, we use historical records of temperature and precipitation on a 0.5° × 0.5° grid that covers Europe[54] to compare average temperature and precipitation in the period 1801-1830 and 1961-1990. The four panels of figure C1 plot average temperature in the years 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four seasons of the year across the 135 cells that cover England and Wales. The four panels of figure C2 repeat the exercise for precipitation, and table C1 reports correlations for the two variables. The data suggest that weather did not change much across England in the last 200 years. In any given season, cells that were on average colder (wetter) in 1800-1830, are still so in 1990-1960. Moreover, the correlation between the two periods of average temperature (precipitation) is always above 99% (98%).

Correlation between weather in 1801-1830
and weather in 1961-1990.

	Temperature	Precipitation
Winter	99.78%	99.48%
Spring	99.45%	98.68%
Summer	99.50%	99.13%
Fall	99.95%	98.69%
Observations	135	135

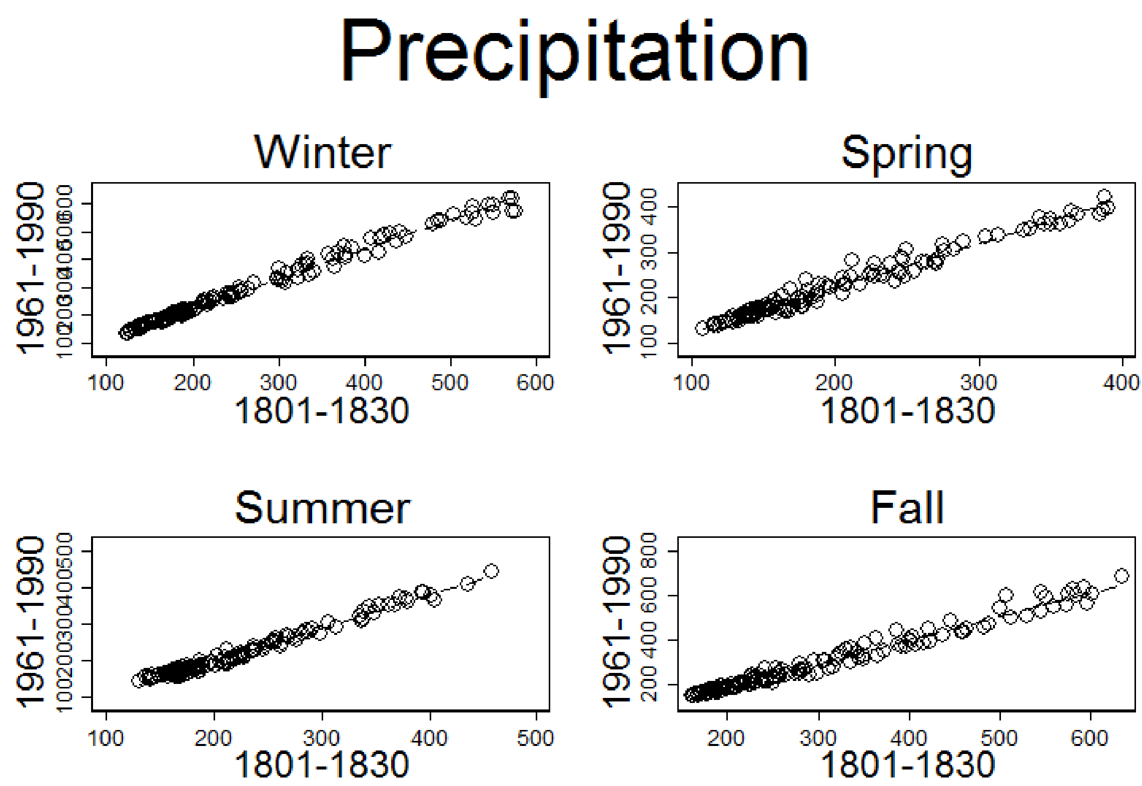
Table C1. Correlation between average weather in the period 1801-1830 and average weather in 1961-1990. The first column reports the correlation for temperature and the second column for precipitation. All correlations are significant at <0.001 level.

[54] Luterbacher *et al.* (2004) and Xoplaki *et al.* (2005) describe the construction of temperature records, and Pauling *et al.* (2006) describe the construction of precipitation data.



Note: temperature is measured in °C.

Figure C1. The figure plots average temperature across England and Wales in the period 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four season of the year. Source: Luterbacher *et al.* (2004) and Xoplaki *et al.* (2005).



Note: precipitation is measured in mm.

Figure C2. The figure plots average precipitation across England and Wales in the period 1801-1830 (on the x-axes) against the average temperature in the period 1961-1990 (on the y-axes) for the four season of the year. Source: Pauling *et al.* (2006).

One possible concern with this analysis is that historical weather data are estimated rather that observed. Moreover, data are available only for separate seasons, not for separate months. To address this concern we perform a second test, using the historical series maintained by the Hadley Centre at the UK Meteorological Office. The office collects monthly precipitation records across England and Wales since 1700. Thus, it allows to compare monthly records obtained from actual observations. We use these data to compare the average monthly precipitation during 1801-1830 with the average monthly precipitation in the years 1961-1990. Figure C3 plots these averages for the two periods along with their 95 percent intervals.

The graph confirms that precipitation did not change much in England over the last 200 years: average yearly precipitation is not significantly different in the 30 years used by FAO relative to the 30 years leading to the Swing riots. Unfortunately, precipitation is the only weather variable for which the Hadley Centre at the UK Meteorological Office preserves historical records. Moreover, these records are admittedly noisy, as they are available only for the whole England. Nevertheless, the analysis of these records, together with the previous analysis, suggest that weather in 1961-1990 is a valid proxy for weather at the beginning of 1800.

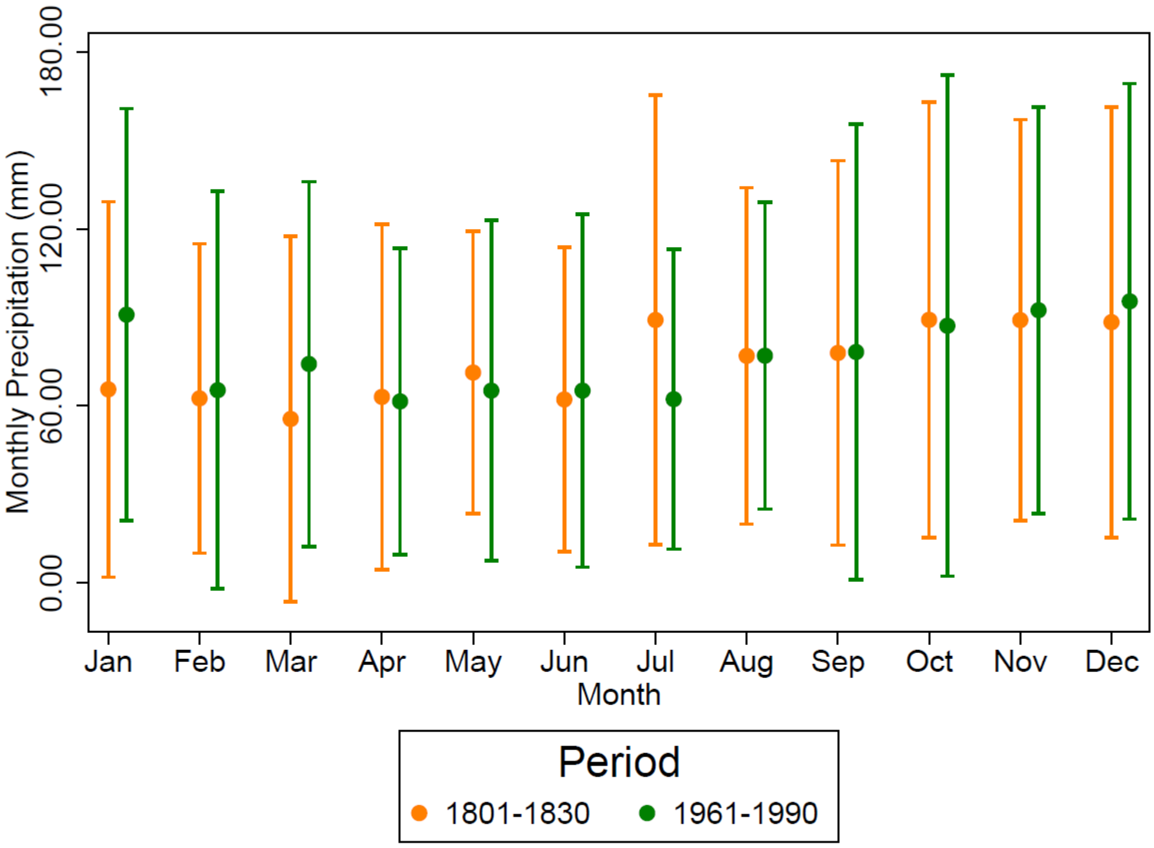


Figure C3. The figure plots the average monthly precipitation across England and Wales over the period 1801-1830 (in orange) and over the period 1961-1990 (in green). The bar identify 95 percent intervals. The average yearly precipitation in 1801-1830 was 891mm: this is not significantly different from the average yearly precipitation in 1961-1990, which was 915m (difference: 23,96mm, s.e.: 24.72).

Source: the Hadley Centre at the Meteorological Office: http://www.metoffice.gov.uk/hadobs/hadukp/.

C.2 Robustness

Dep. var.:	=1 if at least one Swing riot happened in parish						Number of Swing riots		
Estimation method:	Linear probability model			Probit			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Threshing machines	0.084***	0.057***	0.048***	0.084***	0.057***	0.048***	0.371***	0.194***	0.136**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.061)	(0.066)	(0.068)
log(1821 population)	0.065***	0.054***	0.052***	0.065***	0.054***	0.052***	0.520***	0.474***	0.441***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.022)	(0.053)	(0.053)
log(Parish area)		0.031***	0.031***		0.031***	0.031***		0.470***	0.461***
		(0.005)	(0.005)		(0.005)	(0.005)		(0.065)	(0.065)
% families in agriculture		-0.037**	-0.042**		-0.037**	-0.042**		0.068	-0.026
		(0.017)	(0.017)		(0.017)	(0.017)		(0.206)	(0.210)
log(sex ratio)		-0.042**	-0.038**		-0.042**	-0.038**		-0.473*	-0.553**
		(0.019)	(0.019)		(0.019)	(0.019)		(0.265)	(0.268)
log(distance to Elham)		-0.021	0.004		-0.021	0.004		0.057	0.020
		(0.013)	(0.012)		(0.013)	(0.012)		(0.074)	(0.075)
log(dist. to newspaper)		-0.011**	-0.013**		-0.011**	-0.013**		-0.020	-0.008
		(0.005)	(0.006)		(0.005)	(0.006)		(0.053)	(0.057)
Abnormal precipitation, spring 1830		0.000	-0.000		0.000	-0.000		-0.004	-0.011*
		(0.000)	(0.000)		(0.000)	(0.000)		(0.005)	(0.006)
Abnormal precipitation, summer 1830		-0.001***	-0.001***		-0.001***	-0.001***		-0.015***	-0.007**
		(0.000)	(0.000)		(0.000)	(0.000)		(0.003)	(0.003)
Abnormal temperature, fall 1830		-1.072***	-0.932***		-1.072***	-0.932***		-10.348***	-5.788***
		(0.133)	(0.153)		(0.133)	(0.153)		(1.292)	(1.730)
Constant	-0.261***	-0.165**		-0.261***	-0.165**		-4.633***	-8.070***	
	(0.018)	(0.071)		(0.018)	(0.071)		(0.144)	(0.838)	
Region fixed effects (5)			✓			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099
R-squared	0.059	0.120	0.129						
Pseudo R-squared				0.059	0.120	0.129	0.102	0.215	0.228

Table C2. Robustness to different estimation methods. Columns 1-6 report estimates of equation (1) and (2); when the dependent variable is a 0-1 indicator for whether Swing riots happened in the parish. Columns 1-3 report estimates from a linear probability model and columns 4-6 report estimates from a probit model. Columns 7-9 report estimates of equation (1) and (2) estimated with Poisson regression: the dependent variable in these regressions is the number of Swing riots in a parish. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Threshing machine ads			Number of Swing riots					
Equation:	First stage			Reduced form			Two-stages least squares		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
"Threshing machine" ads							5.727***	4.385***	4.851***
							(1.371)	(1.130)	(1.230)
log(pot. yield wheat - low ins) × log(accumulation flow)	0.047***	0.049***	0.045***	0.267***	0.216***	0.220***			
	(0.013)	(0.014)	(0.010)	(0.071)	(0.044)	(0.038)			
log(pot. yield wheat- low ins)	-0.059	-0.054	-0.083**	-0.278	-0.389***	-0.470***	0.059	-0.151	-0.067
	(0.045)	(0.051)	(0.033)	(0.263)	(0.145)	(0.116)	(0.125)	(0.128)	(0.088)
log(accumulation flow)	-0.018***	-0.019***	-0.016***	-0.111***	-0.084***	-0.084***	-0.008	-0.002	-0.008
	(0.005)	(0.006)	(0.004)	(0.030)	(0.018)	(0.015)	(0.010)	(0.008)	(0.009)
log(1821 population)	0.031***	0.016***	0.014***	0.211***	0.151***	0.142***	0.031	0.080***	0.076**
	(0.003)	(0.004)	(0.004)	(0.014)	(0.017)	(0.017)	(0.042)	(0.029)	(0.030)
log(Parish area)		0.023***	0.027***		0.099***	0.106***		-0.002	-0.026
		(0.005)	(0.005)		(0.021)	(0.021)		(0.037)	(0.043)
% families in agriculture		-0.024	-0.042***		-0.097*	-0.131***		0.007	0.074
		(0.016)	(0.016)		(0.051)	(0.050)		(0.085)	(0.098)
log(sex ratio)		-0.039***	-0.019		-0.122***	-0.097**		0.050	-0.007
		(0.014)	(0.014)		(0.046)	(0.047)		(0.085)	(0.084)
log(distance to Elham)		-0.003	0.060***		-0.319***	-0.185***		-0.307***	-0.479***
		(0.004)	(0.008)		(0.037)	(0.047)		(0.038)	(0.094)
log(dist. to newspaper)		-0.008	-0.008		-0.014	-0.019		0.020	0.022
		(0.006)	(0.006)		(0.016)	(0.018)		(0.029)	(0.035)
log(potential yield grass)		0.101***	0.112**		0.152	0.339**		-0.293	-0.203
		(0.039)	(0.044)		(0.121)	(0.141)		(0.240)	(0.291)
Region fixed effects (5)			✓			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099
R-squared	0.021	0.023	0.048	0.062	0.092	0.101			
F-stat excluded instrument	12.5	11.8	18.0						
Rubin-Anderson test (*p*)							0.000	0.000	0.000

Table C3. Robustness to the definition of wheat suitability. Columns 1-3 report estimates of equation (3); columns 4-6 report estimates of equation (4) and columns 7-9 report two-stages least squares estimates of equations (1) and (2). In all regression we use potential yield of wheat calculated under the assumption of "low" level of inputs. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Equation:	OLS			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)
"Threshing machine" ads	0.288	0.269	0.217			
Huber-White robust s.e.	(0.067)***	(0.067)***	(0.067)***			
Conley s.e.: cutoff 20 Km	(0.071)***	(0.070)***	(0.069)***			
Conley s.e.: cutoff 50 Km	(0.091)***	(0.089)***	(0.081)***			
Conley s.e.: cutoff 100 Km	(0.106)***	(0.102)***	(0.085)**			
Clustered s.e.: closest newspaper city	(0.081)***	(0.079)***	(0.076)***			
log(pot. yield wheat) × log(accumulation flow)				0.218	0.193	0.209
Huber-White robust s.e.				(0.082)***	(0.052)***	(0.045)***
Conley s.e.: cutoff 20 Km				(0.084)***	(0.057)***	(0.050)***
Conley s.e.: cutoff 50 Km				(0.095)**	(0.070)***	(0.064)***
Conley s.e.: cutoff 100 Km				(0.099)**	(0.079)**	(0.074)***
Clustered s.e.: closest newspaper city				(0.097)**	(0.071)***	(0.067)***
log(1821 population)	✓	✓	✓	✓	✓	✓
Parish-level characteristics		✓	✓		✓	✓
log(pot. yield) & log(acc. flow)				✓	✓	✓
Region fixed effects (5)			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099

Table C4. Robustness to spatial correlation. Columns 1-3 report OLS estimates for equations (1) and (2). Columns 4-6 report estimates of the reduced form regression (equation 4). We report the point estimates and the Huber-Eicker-White robust standard errors on the first two rows (identical to those shown in Tables 3 and 5); standard errors calculated with the Conley (1999) formula on rows 3 through 5 and then those clustered at the level of the closest city with a newspaper.

Dep. var.:	Number of Swing riots		Number of machine ads		Number of Swing riots			
Equation:	OLS		First stage		Reduced form		Two-stages least squares	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
"Threshing machine" ads	0.216***	0.193***					5.095***	4.851***
	(0.069)	(0.069)					(1.397)	(1.254)
log(pot. yield wheat) × log(accumulation flow)			0.038**	0.043***	0.194***	0.208***		
			(0.014)	(0.011)	(0.056)	(0.049)		
log(potential yield wheat)			-0.042	-0.074**	-0.250	-0.322*	-0.035	0.035
			(0.049)	(0.035)	(0.210)	(0.177)	(0.116)	(0.097)
log(accumulation flow)			-0.050***	-0.055***	-0.255***	-0.271***	0.000	-0.005
			(0.018)	(0.014)	(0.074)	(0.065)	(0.010)	(0.010)
Parish-level characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects (5)		✓		✓		✓		✓
Observations	9,355	9,355	9,353	9,353	9,353	9,353	9,353	9,353
R-squared	0.096	0.101	0.022	0.048	0.091	0.100		
F-stat excluded instrument			7.6	15.2				
Rubin-Anderson test (*p*)							0.001	0.000

Table C5. Robustness to restricting the sample to the parishes within 50 kilometers from the closest newspaper. Columns 1-2 report estimates for the OLS regression (equations 1 and 2). Columns 3-4 report estimates of the first stage regression (equation 3). Columns 5-6 report estimates of the reduced form regression (equation 4). Columns 7-8 report estimates for equations (1) and (2) with two-stages least squares. The dependent variable is the number of Swing riots in the parish in columns 1-2 and 5-8 and the number of advertisements that mention a "threshing machine" in each parish on columns 3-4. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of Swing riots		Number of machine ads		Number of Swing riots			
Equation:	OLS		First stage		Reduced form		Two-stages least squares	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
"Threshing machine" ads	0.262***	0.211***					4.524***	4.303***
	(0.068)	(0.068)					(1.208)	(1.138)
log(pot. yield wheat) × log(accumulation flow)			0.046***	0.053***	0.206***	0.229***		
			(0.014)	(0.012)	(0.063)	(0.057)		
log(potential yield wheat)			-0.072	-0.108***	-0.281	-0.365*	0.043	0.099
			(0.049)	(0.035)	(0.239)	(0.205)	(0.103)	(0.105)
log(accumulation flow)			-0.060***	-0.069***	-0.271***	-0.301***	-0.001	-0.005
			(0.019)	(0.016)	(0.085)	(0.076)	(0.010)	(0.009)
Parish-level characteristics	✓	✓	✓	✓	✓	✓	✓	✓
Region fixed effects (5)		✓		✓		✓		✓
Observations	9,153	9,153	9,150	9,150	9,150	9,150	9,150	9,150
R-squared	0.091	0.099	0.023	0.049	0.092	0.101		
F-stat excluded instrument			10.2	19.7				
Rubin-Anderson test (*p*)							0.001	0.000

Table C6. Robustness to excluding all parishes in Wales. Columns 1-2 report OLS estimates for equations (1) and (2). Columns 3-4 report estimates of the first stage regression (equation 3). Columns 5-6 report estimates of the reduced form regression (equation 4). Columns 7-8 report estimates for equations (1) and (2) with two-stages least squares. The dependent variable is the number of Swing riots in the parish in columns 1-2 and 5-8 and the number of advertisements that mention a "threshing machine" in each parish on columns 3-4. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dep. var.:	Number of Swing riots (August 1830-April 1831)								
Equation:	OLS			Reduced form			Two-stages least squares		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
“Threshing machine” ads	0.224***	0.240***	0.174***				4.391***	3.711***	3.590***
	(0.061)	(0.061)	(0.061)				(1.317)	(1.039)	(0.922)
log(pot. yield wheat) × log(accumulation flow)				0.170**	0.141***	0.156***			
				(0.068)	(0.042)	(0.035)			
log(potential yield wheat)				-0.061	-0.181	-0.263**	0.136	-0.046	0.006
				(0.264)	(0.157)	(0.124)	(0.119)	(0.092)	(0.071)
log(accumulation flow)				-0.231**	-0.185***	-0.203***	-0.010	-0.003	-0.006
				(0.090)	(0.055)	(0.046)	(0.008)	(0.007)	(0.007)
log(1821 population)	✓	✓	✓	✓	✓	✓	✓	✓	✓
Parish-level characteristics		✓	✓		✓	✓		✓	✓
Region fixed effects (5)			✓			✓			✓
Observations	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099	10,099
R-squared	0.077	0.041	0.084	0.046	0.077	0.086			
Rubin-Anderson test (*p*)							0.012	0.001	0.000

Table C7. Robustness to timing of the riots: only episodes between August 1830 and April 1831. Columns 1-3 report OLS estimates for equations (1) and (2). Columns 4-6 report estimates of the reduced form regression (equation 4). Columns 7-9 report two-stages least squares estimates of equations (1) and (2). The dependent variable is the number of Swing riots that happened between August 1830 and April 1831. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.