Structural factors or contagion?
The Swing riots and the drivers of social unrest*

Toke Aidt Gabriel Leon

Cambridge King's College London

Word count: 9,727

(excluding online appendix)

Abstract

Structural factors and contagion are the main drivers of social unrest, but which is more important? To address this question we consider the English Swing riots of 1830-31. The rural nature of the riots and the limited mobility of agricultural workers means that we can use clearly-observable spatial variation in a large number of structural factors to estimate their role in triggering the riots. We then quantify the importance of these factors relative to that of contagion. We find that factors related to the type of agriculture and the capacity for organization were significant in triggering riots, and that contagion on average magnified their impact by a factor of 2.65. Our historical data allow us to address a key question in the conflict literature, while improving our understanding of a period that was critical to the development of British democracy.

Keywords: Riots, structural factors, contagion, diffusion, conflict, Captain Swing.

*Corresponding author: Gabriel Leon, Department of Political Economy, King's College London, Bush House (NE), 30 Aldwych, London WC2B 4BG, UK; e-mail: gabriel.leon@kcl.ac.uk. Toke Aidt, Faculty of Economics, University of Cambridge, Austin Robinson Building, Sidgwick Avenue, CB3 9DD Cambridge, UK; email: tsa23@econ.cam.ac.uk. We wish to thank Ali Hemmingway, Jay Lee, Simon Pittaway, Naomi Roba, Andriy Levitskyy and Arjun Dwesar Kumar for excellent research assistance. We are also grateful to the Cambridge Group for the History of Population and Social Structure for providing us with shape files for the maps of the ancient counties and parishes (ESRC Grant RES-000-23-1579), access to the digitized 1831 Population Census (ESRC Grant RES-000-23-1579), and access to part of the digitized 1815 poor law returns and the directory of stage coach services 1836 (Leverhulme Trust, RPG-2013-093). We thank Mauricio Rodriguez Acosta for sharing with us data on the location of police forces in England and Wales. The research was supported by the British Academy (BA grant JHAG097). We wish to thank the seminar audiences at King's College London, Essex, Oslo, Nottingham, Munich, Sheffield, Leicester, Rennes, Barcelona, Birmingham, UCL, Alghero, LSE, Oxford, Universitat Pompeu Fabra, Glasgow, York, NEPS, EPCS, Silvaplana, and EPSA for their comments. We thank Barry Eichengreen, Marco Manacorda, Andrea Tesei, Vincenzo Bove, Ruben Enikolopov, Antonio Ciccone, Stephane Wolton, Jordi Blanes i Vidal, Lena Gerling, Carlos Velasco, Pramila Krishnan, Elena Seghezza, Jean-Paul Azam, Nadia McCloud-Rose and James Fenske for their helpful suggestions, and Leigh Shaw-Taylor for many insightful discussions.

1 Introduction

Episodes of social unrest, including riots and protests, are common across the world in both developing and developed countries. Social science provides two sets of complementary explanations for why social unrest takes place: the first emphasizes *structural factors*, while the other emphasizes *contagion*.[1] The relative importance of structural factors and contagion is a key question in the study of conflict and democratization (e.g. Gleditsch and Ward, 2006; Buhaug and Gledistch, 2008), yet in most settings it is difficult to measure the relevant structural factors because participants are unknown or travel in from other locations.[2] This then means that it is difficult to estimate the impact that specific factors have on participation and their importance relative to that of contagion. We overcome this challenge by using historical data.

We focus on a specific incident of social unrest, the Swing riots of 1830-1831, to investigate the structural factors that drove the occurrence of riots in a location (a parish) and the importance of these structural factors relative to contagion. We focus on riots because they are often localized and take place in different locations at different times, allowing us to treat them as a number of discrete events that can be easily observed. Our historical focus is advantageous because ease of transport today means that people can travel considerable distances to participate in a riot, making it impossible to associate the structural factors of a particular location – including social and economic fundamentals, organizational capacity, connectedness and repression – to the conditions of those who riot in that locality.[3]

The Swing riots allow us to address this problem: the rural and local nature of the riots and the restrictions on mobility that existed at the time allow us to assign parish-specific factors to each riot event in a way that is not possible with more recent data. These factors can be treated as exogenous because they predate the riots and likely remained unchanged

[1]Hays et al. (2010) distinguish between common exposure (the structural factors) and contagion (the fact that riots may happen because other riots were taking place nearby.

[2]Examples of the first literature include Fearon and Laitin (2003); Collier and Hoeffler (2004); Montalvo and Reynal-Querol (2005); Esteban and Ray (2011); Campante and Chor (2012b); Finkel et al. (2015); Scacco (2016); Dahlum and Wig (2017); Osorio et al. (2017); Castañeda Dower et al. (2018); examples of the second include Granovetter (1978); Kuran (1989); Lohmann (1994); Salehyan and Gleditsch (2006); Buhaug and Gledistch (2008); Metternich et al. (2016). There is a related literature in sociology that looks at the factors that cause protests to spread; e.g. Andrews and Biggs (2006, 2015).

[3]For example, there is evidence that in the 2011 London riots many participants traveled to the riot locations (Baudains et al., 2013).

in the relatively short duration of the uprising. This enables us to examine which factors influenced whether a parish experienced a riot, and to quantify the importance of these factors *relative* to contagion.[4] For this we use a large dataset we collected that tracks the evolution of the Swing riots over 40 weeks in 1830-31 across more than 10,000 parishes in England.

We study the spatial variation in the total number of riots that took place in different parishes throughout the uprising. This cross-sectional analysis allows us to evaluate the parish-specific time-invariant structural factors and their importance relative to contagion, something that cannot be done within a fixed-effects panel framework.[5] We consider four groups of observable factors related to social and economic conditions, organizational capacity, connectedness of the parish to the outside world, and repression. We find that parishes where agriculture was a large part of the local economy and those with high organizational capacity experienced more riots. This is consistent with the interpretation that both grievances and organization play a role in triggering these events. We also find strong evidence of contagion. Combining these results, we find that contagion magnified the impact of a change in a parish-level fundamental by an average factor of 2.65.

Our focus on the Swing riots provides us with a credible identification strategy, but comes at the expense of being specific. However, the role of structural change in triggering riots and protests is as salient today as it was in the early nineteenth century: recent evidence shows a link between the presence of labor-saving machinery and the Swing riots (Caprettini and Voth, 2017), and so the situation of these rioting farm laborers is not unlike that of current ex-miners in the north of England or factory workers in the American Midwest. The Swing riots are of substantive historical importance too: they made people fear that England was close to revolution (e.g., McCarthy, 1882, p. 69) and thus played a critical role in the passage of the Great Reform Act, a critical juncture in British history (Aidt and Franck, 2015).

[4] We contribute to a literature that uses ecological data to study social movements and popular uprisings, including Biggs and Knauss (2012), Kawalerowicz and Biggs (2015) and Brooke and Ketchley (2018).

[5] Aidt et al. (2018) exploits variation in the timing of the riots to study specific diffusion mechanisms, but cannot estimate the role of structural factors because these are time-invariant and hence are removed by parish fixed-effects.

The rest of this paper is organized as follows. Section 2 introduces the historical context. Section 3 offers a theoretical framework, while section 4 discusses the data. Section 5 presents the results from our empirical analysis. Section 6 offers some concluding remarks. The online appendix describes the data sources and reports additional estimation results.

2 Historical background

The Swing riots were a rural uprising in the English countryside.[6] The riots started in Kent, gained momentum in August 1830, and peaked in late November; by March 1831 they had returned to their initial low level. Nearly 3000 riots took place, and they included the burning of barns and ricks, destruction of threshing machines, robbery and forced levies of money, assaults on poor law officials, wage and tithe riots, and anonymous threatening letters.[7] The map in Figure 1 shows the spatial distribution of the riots and reveals that they were concentrated in the cereal-producing areas of the south-east, in the Midlands and in East Anglia, while the dairy-producing areas in Cornwall, Wales and the north of England were less affected.

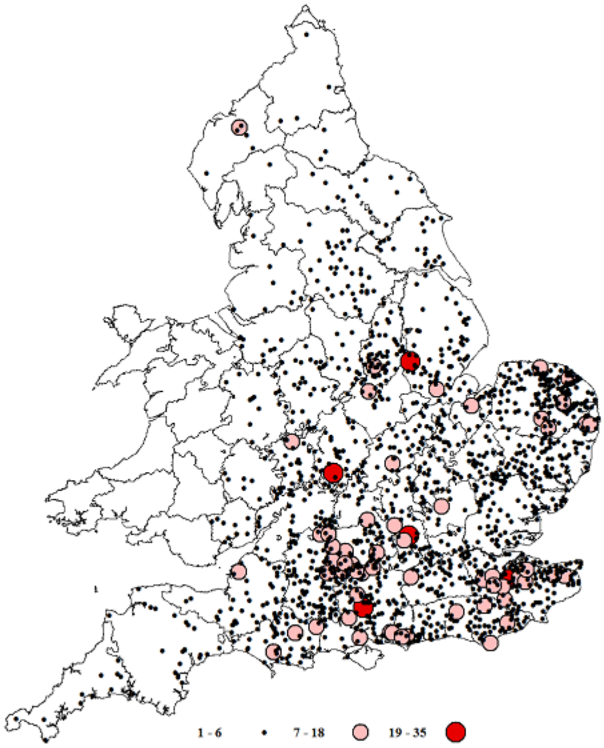
The Swing rioters were primarily farm laborers employed by tenant farmers on daily or weekly wage contracts.[8] Despite significant out-migration to the new industrial cities, rural unemployment was high throughout the 1820s, especially outside the peak harvest season. Many farm laborers and their families lived in extreme poverty, a situation that was made worse by a failed harvest in 1829 and the adoption of the threshing machine, which took away much of the farm laborers' winter employment. The demands of the Swing rioters were largely economic in nature: higher wages, separation of poor law subsidies from wage payments, and more work. These demands were directed towards local farmers and parish officials.

[6]The riots derived their name from the mythical Captain Swing, whose signature could be found on the threatening letters received by authority figures in the affected areas.

[7]We follow the historiographical literature and refer to these events as riots, acknowledging that some of them (e.g., the Swing letters) may be better described as instances of protest. Table A1 in the online appendix reports the number of occurrences by type.

[8]Yet it is clear from the information about the occupation of the participants (Holland, 2005) that about 16 percent of the 1270 individuals for whom occupation information is available were village craftsmen and traders.

Figure 1: The spatial distribution of the Swing Riots.



Notes: The map shows the location of all recorded Swing riots. The unit of analysis is the parish and the radius of each circle reflects the number of riots in each parish.

The authorities reacted to the riots with both concessions and repression. The local nature of the demands made by the rioters meant that local resolutions could be found in many cases (Jones, 2009). Law enforcement was also a local matter, and the national government's main contribution was to station some troops in the larger towns in the affected areas. After an initially lacklustre response that allowed the riots to spread for months, a change in government led to a more robust national repression effort with the result that by December 1830 about 2000 rioters had been arrested. Many of them were eventually sentenced to death or transported to Australia.

3 Framework and hypotheses: structural factors or contagion?

The literature on social unrest and conflict emphasizes two main drivers: structural factors and contagion. The structural theories of conflict emphasize how factors including poverty, income shocks and ethnicity can affect participation, while theories that focus on contagion consider how the participation of others may affect an individual's decision to join an uprising. Our aim is to assess which structural factors played a significant role in triggering riots and quantify the importance of these factors relative to contagion. In the rest of this section we draw from the work of social historians to develop specific hypotheses about the impact of particular structural factors and contagion.

3.1 Structural theories of conflict and the Swing riots

There is general agreement among social historians that by 1830 relative deprivation, poverty, systematic underemployment induced by structural changes, and adverse movements in agricultural prices had created an explosive situation in the countryside (Hammond and Hammond, 1912; Thompson, 1963; Hobsbawm and Rudé, 1973; Charlesworth, 1979; Tilly, 1995). They highlight four sets of structural factors: (i) the social and economic fundamentals of the parish in which the rioting farm laborers lived and worked; (ii) organizational capacity, (iii) the connectedness of the parish to the outside world, and (iv) repression.

3.1.1 Social and economic fundamentals

A large number of factors have been considered by the literature, ranging from poverty and income shocks (Collier and Hoeffler, 2004; Miguel et al., 2004; Chaney, 2013; Dorsch and Maarek, 2015; Kawalerowicz and Biggs, 2015; Aidt and Leon, 2016), to the demographic structure of a society (Urdal, 2006; Campante and Chor, 2012a,b) and ethnic or religious tensions (Fearon and Laitin, 2003; Montalvo and Reynal-Querol, 2005; Forsberg, 2008; Scacco, 2008; Esteban and Ray, 2011; Esteban et al., 2012; Mitra and Ray, 2014; Iyer and Shrivastava, 2016). DiPasquale and Glaeser (1998) show that social conditions influenced riot participation in Los Angeles in 1992.

According to Hammond and Hammond (1912, Ch. 11) and Hobsbawm and Rudé (1973, Ch. 4), spatial variation in socio-economic conditions, related to the local agricultural economy (cereal versus dairy production), the number of people working in agriculture and manufacturing, the number of men, the availability of common land and the generosity of the poor laws (the welfare system) all played a role. Hammond and Hammond (1912, p. 85) view the Enclosure Acts of rural England as the most important structural factor triggering the riots. These acts of parliament, which applied to particular localities, reduced the access that the rural poor had to common land, thereby increasing economic hardship and discontent. Under the poor law system each parish was responsible for its own poor, and payments and wage subsidies were funded out of the the poor rate, which was a tax levied on local property owners (Boyer, 1990).[9] The administration of this system had evolved organically and different practices and norms had emerged locally, creating large differences in the generosity of support across parishes (Marshall, 1968).

3.1.2 Organizational capacity

Many theories of conflict highlight that two complementary inputs are needed to trigger social conflict: "brain" and "muscle". The first are needed to organize the violence, while the second are needed to carry it out.[10]

The English parishes had a large supply of "muscle" recruited from among the landless farm laborers, but there was a great deal of variation in the supply of "brain". Charlesworth (1979, 1983), Tilly (1995, Ch. 7) and Thompson (1963, p.225-7) stress the essential part that local leaders, typically belonging to a different social class than the farm laborers, played in initiating riots in a parish. These local leaders, willing and able to overcome the collective action problem, were more likely to be found in large and economically diverse parishes with many economically independent and literate individuals (artisans, craftsmen, traders, and shopkeepers). Our conjecture is that those parishes were more likely to experience riots.[11]

[9] On average about one fifth of the farm laborers' income came from this subsidy, restricting labor mobility as laborers lost their right to aid when they moved to another parish (Marshall, 1968).

[10] These include Esteban and Ray (e.g., 2011); Esteban et al. (e.g., 2012); Mitra and Ray (e.g., 2014) and Olson (1965).

[11] This hypothesis is supported by several well-documented cases where riots were clearly led by village radicals. For example, in November 1830 a radical shoemaker from Maidstone in Kent led "two to three hundred rioting agricultural labourers demanding cash contributions from various targets and making political speeches" (Well, 1997, p. 38). However, the question of national leadership and conspiracy has been investigated and dismissed by many others (Hobsbawm and Rudé, 1973; Jones, 2009).

3.1.3 Connectedness

Radio, television and social media have played an important role in many recent episodes of social unrest, including ethnic genocide in Rwanda (Yanagizawa-Drott, 2014), the violent confrontations during the Arab spring revolutions (Hassanpour, 2014; Sabadello, 2012; Lotan et al., 2011) and the election-related protests in Russia in 2011 (Enikolopov et al., 2016). Information can flow quickly and reach large audiences through these media, and this makes it easier for individuals to coordinate.[12] Recent work has examined the importance of rail links (Brooke and Ketchley, 2018) and the coach network (Aidt et al., 2018) in the spread of social movements and riots.

The Swing riots predate modern communication technologies: the telegraph had only recently been invented and was only in military use, and the expansion of the railroad did not happen until a decade after the riots. The farm laborers' universe was the parish in which they resided, a few of the neighboring parishes where they might have family links, and the local market town (Hobsbawm and Rudé, 1973, p. 56-57). Their network of connections was local. Yet connections to the wider world mattered and some parishes were better connected than others by virtue of their proximity to markets and fairs (Hobsbawm and Rudé, 1973, p. 188), their location along the coach network (Albert, 1972), or their access to a local newspaper that recycled London news of local interest (Barker, 2000).

3.1.4 Repression

Participation in riots and protests is usually affected by the risk of arrest, injury or death. For example, evidence from the 2011 London riots shows that rioters reacted to increases in police presence by systematically relocating their activities to other parts of the city (Davies et al., 2013).

In the 1830s law and order was the responsibility of local magistrates, but they had very few resources at their disposal. They relied on volunteers, many of whom were initially reluctant to help. Outside of London, about 88 towns had established police forces by 1830, but they were small and set up to police urban areas only (Jones, 1982). The regular army

[12]See Sabadello (2012) for an overview of this literature and Little (2016) for a discussion of which aspects of the coordination problem social media can help resolve.

was small and scattered between the ports, the capital and some of the larger provincial towns. This generated large spatial differences in the response from the magistrates, and Hobsbawm and Rudé (1973, p. 189) argue that these differences encouraged riots in areas with little or no law enforcement (e.g., in Norfolk), while hindering them in areas with more repression (e.g, Hampshire and Wiltshire).

3.2 Theories of contagion

Theories of contagion seek to explain how unrest spreads. Granovetter (1978) shows how an individual's decision to participate can set in motion a process where instigators draw others in. Kuran (1989) uses this same logic to explain revolutions while Lohmann (1993, 1994) extends it into a theory of information cascades. Much attention has been devoted to the study of spatial contagion of violent intra- and inter-state conflict (e.g., Sambanis, 2002; Collier and Hoeffler, 2004; Hegre and Sambanis, 2006; Salehyan and Gleditsch, 2006; Buhaug and Gledistch, 2008; Metternich et al., 2016), to spatial contagion of drug-related violence (Osorio, 2015) and to the spread of social unrest, including the 2011 London riots (Baudains et al., 2013; Davies et al., 2013), the 1965 Watts riots (Stark et al., 1974) and the Swing riots (Aidt et al., 2018).

Social historians have emphasized the localized, spatial contagion of the Swing riots: riots nearby in other parishes affected a parish's propensity to riot. This emphasis on the *local* is natural because news and people moved slowly. Hobsbawm and Rudé (1973, p. 189) argue that the spread of the riots was facilitated by the spatial structure of personal contacts between nearby places, so that spatial effects were highly localized. The potential rioters in one parish would observe riots nearby and learn about their outcomes or consequences.[13]

[13] An example of how information about law enforcement may have encouraged the spread of the riots is suggested by the letter from a clergy-man from Tunbridge Wells to the government, in which he appealed for the government to punish rioters because otherwise "their impunity increases their hardihood and makes them suppose either that Government is indifferent to their proceedings or is too weak to put them down" (Home Office 52/8, Letter of 22 November 1830).

4 Data and Measurement

Our data on the Swing riots comes from Hobsbawm and Rudé (1973, Appendix II), the Family and Community Historical Research Society (Holland, 2005) and Griffin (2012). Their primary sources were London-based periodicals, Home Office documents and other national archival sources, as well as information from local archives and newspapers. The data record the name of the location (parish/township/hamlet) and county in which the riots took place, the date, and in some cases a short description of the event. The riots data is almost certainly a complete record of the riots that were reported, and although some incidents may not have been reported at the time, we have no reason to believe that our sample is unrepresentative.[14] We geo-referenced each riot and aggregated the daily observations to a total for each parish, covering the 40 weeks between June 28 1830 and April 3 1831 for the 10,335 English parishes.[15]

The data on structural factors comes from a variety of primary and secondary sources, including the 1831 Population Census of Great Britain. These data are recorded at the parish level and are available for up to 10,335 English parishes. They do not exhibit any time variation over the course of the 40 weeks of the Swing riots, and so we focus on cross-sectional specifications. We follow the historiographical literature discussed in section 3 and divide the parish-specific, time-invariant structural factors into four categories (see the online appendix for precise definitions of the variables and sources).

The first category captures the social and economic structure of the parish. We use Caird (1852)'s division of England into four agricultural regions, along a north-south and an east-west axis, to capture differences in agricultural production.[16] The north-south axis demarcates the eastern counties dominated by cereal production (mostly grain and wheat) from those in the west dominated by dairy farming. The east-west line, which runs through Shropshire via Leicestershire to Lincolnshire, demarcates the relatively high-wage counties in the north from the low-wage counties in the south. Based on this, we code three indicator

[14] One possibility is that riots that took place in parishes near locations that printed newspapers were more likely to be reported. In the online appendix we show evidence that suggests that this was not the case.

[15] We have no information on riots in Scotland and do not have data on many of the structural factors for Wales.

[16] The online appendix shows a digitized version of this map.

variables (**High wage, cereal**; **Low wage, dairy**; and **Low wage, cereal**) to capture variations across the four agricultural regions of England.[17] We measure the employment structure of a parish by recording the number of families engaged in agriculture (**families in agriculture**), the number of tenant farmers and landowners (**farmers**), the number of individuals employed in manufacturing (**manufacturing workers**) and the number of adult males (**males**), all of which proxy for the supply of "muscle". We include a dummy variable **enclosed before 1830** that codes the history of enclosure of common land in the parish and equals one if the parish had enclosed prior to 1830 (Gonner, 1912; Tate, 1978). We also include a variable (**wealth**) that measures the aggregate value of property in 1815; we use this as proxy for differences in the generosity of the poor law subsidies (since these were calculated relative to the value of property).

To measure organizational capacity we include measures of the area of the parish (**area**) and total population (**population**), since the literature suggests that these would be more likely to have potential organizers. We also include the number of people employed in trade and handicraft (**traders and craftsmen**) and in the professions including law, medicine and teaching (**professionals**), since these are the groups that were most likely to produce the "brains". Furthermore, civic groups and individuals could petition parliament directly in relation to local or national issues, and it is reasonable to assume that the parishes with a higher petition activity were also those that had a critical mass of local leaders. The variable **petitions**, coded from the Journals of the House of Commons, records the number of petitions sent to parliament between 1828 and 1831 that related to the three main social issues of the period: slavery, Catholic rights and parliamentary reform (House of Commons, 1831).

The third category captures how connected each parish was to the outside world. We use several proxies to capture this connectedness. The variable **marketN** records whether a parish was within a 10km distance of a town with a weekly or bi-weekly market (Owen, 1827). The variable **coachstopN** records if a parish was within a 10km distance of a stop on the stage coach network (Bates, 1969). The variable **newspaperN** records whether a parish was within a 10km distance of a town that published a local or regional newspaper

[17]The omitted region is **High wage, dairy**.

(House of Commons, 1833). Being close to a regular market, a coach stop, or a location where a newspaper was published meant that the parish was connected to the outside world.

The fourth category relates to repression. We capture this through two variables: **distance to garrison** and **policeN**; the first measures the distance to the nearest garrison (War Office, 1830), while the second is a dummy that equals 1 if the parish is located within a 10km radius of a municipal borough with a police force (Clark, 2014). These variables are chosen because the effectiveness with which the local magistrates could respond to the riots likely depended on whether there was an army garrison or a police force nearby.

Finally, to measure contagion we used GIS software to compute 10km neighborhoods around each parish, and then used them to calculate the total number of riots that took place in each parish's neighborhood.[18] The 10km radius, which corresponds to a walking distance of about 2-3 hours, corresponds to the extent of the area commonly frequented by agricultural workers (Hobsbawm and Rudé, 1973, p. 212).[19]

5 Structural factors or contagion?

We now establish the importance of parish-specific, time-invariant structural factors and contagion. The structural factors exhibited no time variation during the 40 weeks of the uprising, and so we must use the cross-sectional variation in the total number of riots experienced by different parishes during the whole 40-week period. The unit of analysis is the parish, of which there were 10,335 in England. The baseline specification is

$$\mathbf{riots} = \alpha\iota + \beta_1 \times \mathbf{W} \times \mathbf{riots} + \mathbf{fundamentals} \times \gamma + \mathbf{county} \times \delta + \mathbf{u}, \tag{1}$$

which is a standard spatial autoregressive model where **riots** is a $n \times 1$ vector where n is the number of parishes and element i (denoted $\mathbf{riots}_i$) equals the total number of riots that took place in parish i between Monday, 28th June 1830 and Sunday, 3rd April 1831. On the right hand side, the first term includes a scalar α and a unit vector ι of length n. The second term includes the scalar β_1, the $n \times n$ row-normalized weight matrix $\mathbf{W}$ with

[18] In the online appendix we show that our results are robust to using a 20km radius to define these neighborhoods.

[19] Table A2 in the online appendix reports the descriptive statistics for these variables.

non-zero entries corresponding to parishes with centroids within 10km of each other, and all other entries set to 0.[20] This is the spatial lag and it captures contagion: for a parish i it records the average number of riots that took place in parishes within 10km.[21] The matrix **fundamentals** has dimension $n \times k$ where k is the number of structural factors included, with row i corresponding to the value of the factor for parish i, while $\gamma \times 1$ is a vector of length k with its elements corresponding to the coefficients on the factors. We consider 19 parish-specific factors related to demographic and economic conditions, organizational capacity, connectedness of the parish to the outside world and repression. The matrix **county** has dimension $n \times c$ where c is the number of counties, with element (i, j) being equal to 1 if parish i is in county j and 0 otherwise, while δ is a $c \times 1$ vector with the county fixed effects. Many important correlated effects (such as shared characteristics between clusters of parishes or exposure to the same law enforcement shocks) are picked up by the county fixed effects. The error is given by the $n \times 1$ vector $\mathbf{u}$.

We conduct the analysis in three parts. First, we investigate the parish-specific structural factors driving the riots in the absence of contagion. This allows us to get a sense for which factors played a role in triggering riots. We then estimate equation (1) restricting attention to the structural factors that we found to be significant and correct for the bias introduced by the inclusion of a lagged dependent variable. Finally, we use these estimates to quantify the importance of the structural factors relative to contagion.

5.1 The parish-specific structural factors

To gain a better understanding of the relationship between the parish-specific fundamentals and the total number of riots in a parish, we begin by using a restricted version of equation (1) where β_1 is set equal to 0. This allows us to estimate the effect of each observable fundamental in the absence of contagion and see which factors are statistically significant. Table 1 presents the results. The specification in column (1) is estimated using OLS and

[20] The diagonal entries are all set to 0, so that a parish is not its own neighbor.

[21] The choice of whether the weight matrix is row-normalized should be done on the basis of theory (Plümper and Neumayer, 2010); we choose to row-normalize because in later specifications we consider the impact that the structural factors in parish i's neighbors may have on riots in parish i, and it makes sense to average these values across neighboring parishes (since it is likely that what matters is the average wealth across parishes, for example, rather than the sum total of their wealth).

Table 1: Parish-specific structural factors

VARIABLES	(1) riots	(2) riots
Social & economic fundamentals		
High wage, cereal	0.071	0.16
	(0.045)	(0.41)
Low wage, dairy	-0.070	-0.58
	(0.068)	(0.56)
Low wage, cereal	0.41	0.55
	(0.16)***	(0.58)
Log **families in agriculture**	0.037	0.20
	(0.022)*	(0.077)***
Log **farmers**	-0.0034	-0.066
	(0.022)	(0.089)
Log **manufacturing workers**	-0.012	0.0075
	(0.0097)	(0.039)
Log **males**	-0.14	-1.16
	(0.096)	(0.69)*
Enclosed before 1830	-0.0068	0.098
	(0.023)	(0.088)
Log **wealth**	-0.021	-0.16
	(0.026)	(0.10)
Organizational capacity		
Log **area**	0.11	0.46
	(0.027)***	(0.12)***
Log **population**	0.12	1.21
	(0.090)	(0.70)*
Log **traders and craftmen**	0.049	0.22
	(0.016)***	(0.090)**
Log **professionals**	0.040	0.0030
	(0.013)***	(0.075)
Log **petitions**	0.083	0.091
	(0.035)**	(0.10)
Connectedness		
MarketN	0.0012	0.0057
	(0.034)	(0.16)
CoachstopN	-0.011	-0.12
	(0.030)	(0.11)
NewspaperN	-0.028	-0.059
	(0.033)	(0.16)
Repression		
Log **distance to garrison**	0.0053	0.12
	(0.026)	(0.11)
PoliceN	0.053	0.26
	(0.030)*	(0.097)***
Observations	9,491	9,491
R-squared	0.17	
Fixed effects	County	County
Standard errors	Conley	Cluster by County
Estimation	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. In column (1) the standard errors are corrected for serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). Column (2) reports results from a Poisson estimator with the standard errors clustered at the county level. The unit of observation is the parish, and element i in the vector **riots** equals the total number of riots in parish i during the 40 weeks of the uprising.

the standard errors are corrected for spatial correlation following the procedure in Conley (1999); the specification in column (2) is estimated using a Poisson estimator that takes into account the count nature of our riots data.[22] Both specifications include county fixed effects so that we exploit variation in parish fundamentals relative to the within-county average. The observable fundamentals can explain 17 percent of the within-county cross-parish variation in riots (column (1)).

We first consider the social and economic fundamentals. We find that parishes located in the low wage, cereal-producing region of England and those with more families employed in agriculture experienced more riots. This is not surprising, since most Swing rioters were concentrated in these areas and belonged to this group of landless farm workers. The number of farmers, people employed in manufacturing and men appear to have no impact. We find that the enclosure of common land before 1830 had no effect on the riots, contrary to the conjecture by Hammond and Hammond (1912). We also find that variations in property values (**wealth**) did not impact on riots despite the fact that this was the tax base upon which the poor law taxes were levied.

Turning our attention to organizational capacity, larger parishes experienced more riots; there is also some weak evidence that population had a positive impact on participation. The number of people employed in trade and in the professions and the number of petitions sent to parliament had a positive and significant impact on participation. This suggests that village-level radicalism may have played a role. As emphasized by Charlesworth (1979), it was the craftsmen, artisans and traders with radical sympathies and knowledge of what was happening in the wider world who possessed the organizational skills to resolve the collective action problem and mobilize the local farm laborers to riot. Our results provide strong evidence in favor of organizational capacity as an important driver of riots.

Connectedness appears to have played no role: we find that parishes near markets, coach stops or newspapers did not experience more riots than other parishes. Finally, we observe that repression, as captured by the proximity to a policy force (**policeN**), had a

[22] The negative binomial is often used when the mean and variance of the outcome variable are different, as is the case here. However, the Poisson conditional fixed effect ML estimator that we use is robust to the violation of this restriction. We implement this using the *ppml* command in Stata (Santos Silva and Tenreyro, 2006).

positive impact on participation. The direction of this effect is somewhat puzzling, as we would have expected the presence of police to reduce participation. However, the police forces were in the process of being created, and so it is likely that these first forces were established in areas where law and order was a serious concern.

5.2 Contagion

We now turn our attention to contagion; this is necessary in order to compare its impact to that of the structural factors. The presence of a spatial lag in equation (1) implies that OLS estimates will be biased and inconsistent, since the spatial lag is mechanically correlated with the error term (Anselin, 1988). To eliminate this source of bias, we estimate the equation with an spatial 2SLS estimator developed by Kelejian and Prucha (1998). This estimator instruments for the spatial lag with three vectors of variables – **fundamentals**, $\mathbf{W} \times$ **fundamentals** and $\mathbf{W^2} \times$ **fundamentals** – where $\mathbf{W}$ is the weight matrix, $\mathbf{W}^2$ is the second spatial lag, and **fundamentals** is a vector of the nine factors we found to be significant in at least one of the specifications reported in Table 1. The intransitive nature of our network, where i and j can be neighbors, j and k can be neighbors, but i and k will often not be, is a sufficient condition to ensure that this instrument set is valid and informative.[23] We use the SHAC version of this estimator, which adjusts the spatial 2SLS errors for heteroskedasticity of unknown form and for spatial autocorrelation (Kelejian and Prucha, 2007).

Columns (1) and (2) in Table 2 report SHAC estimates of β_1. Column (1) shows a specification without any of the structural factors (i.e. setting $\gamma = 0$ but including county fixed effects), while column (2) shows a specification with the nine factors. Column (3) reports maximum likelihood Poisson results that take into account the fact that on the left-hand side we have a count variable. The coefficient on the spatial lag is positive and highly significant in all cases: the total number of riots in a parish is positively associated

[23] More specifically, the exogenous variation is contained in $\mathbf{W^2} \times$ **fundamentals**, since the other two instruments are the own and the neighbors' structural factors (the peer effects literature refers to the latter as the *contextual* effects). For this instrument to bring information that is not already included in the specification, it must be that some of the links it contains are not included already. A sufficient condition for this is that not all second degree neighbors (i.e. neighbors of neighbors) are themselves neighbors. This is equivalent to requiring that the network exhibit some degree of intransitivity.

Table 2: Contagion of the Swing riots

VARIABLES	(1) **riots**	(2) **riots**	(3) **riots**	(4) **riots**
W × **riots**	0.92	0.73	0.49	0.92
	(0.045)***	(0.050)***	(0.062)***	(0.037)***
Log **area**		0.11	0.52	0.12
		(0.044)**	(.066)***	(0.50)**
Log **population**		0.02	1.25	-0.02
		(0.05)	(0.619)**	(0.057)
Low wage, cereal		0.16	0.68	0.11
		(0.028)***	(0.219)***	(0.038)***
Log **families in agriculture**		0.02	0.10	0.006
		(0.010)	(0.64)	(0.011)
Log **traders and craftmen**		0.06	0.24	0.048
		(0.012)***	(0.82)***	(0.012)***
Log **professionals**		0.04	-0.02	0.04
		(0.009)***	(0.56)	(0.009)***
Log **males**		-0.06	-1.21	-0.001
		(0.056)	(0.614)**	(0.065)
Log **petitions**		0.09	0.13	0.097
		(0.024)***	(0.082)	(0.024)***
policeN		0.02	0.15	0.056
		(0.011)*	(0.86)*	(0.019)***
Observations	10,309	10,309	10,042	10,309
Dummies	County	County	County	County
Contextual effects	No	No	No	Yes
Standard errors	Spatial	Spatial	Clustered	Spatial
Estimation	SHAC	SHAC	Poisson	SHAC

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. The unit of observation is the parish, and element i in the vector **riots** equals the total number of riots in parish i during the 40 weeks of the uprising. For a parish i, **W** × **riots** refers to the average number of riots across parishes within 10km of its centroid (excluding riots that happened in i itself). The structural factors we include are those that were statistically significant in at least one of the specifications reported in Table 1. The SHAC estimator used to obtain the coefficients in columns (1), (2) and (4) is implemented with the sphet package in R (see Piras (2010)), using a row-normalized weight matrix where parishes within 10km (Euclidean distance) are considered neighbors. The standard errors reported in these columns are robust to heteroskedasticity and spatial correlation. The coefficients in column (3) are from a Poisson regression estimated using the glmmboot (glmmML) command in R. Column (4) shows a specification with contextual effects (the structural factors in the neighboring parishes). This allows the average of each of the nine fundamentals in the parishes within 10km of parish i to influence riots in i. Table A3 in the supplementary material reports the coefficients for these contextual effects.

with the total number of riots nearby, showing that riots cluster in space. The fact that the point estimates on the spatial lag are relatively insensitive to whether the structural factors are included suggests that the spatial lag and the structural factors pick up different aspects of the data-generating process.

The baseline spatial autoregressive model in equation (1) does not include spatial lags of the structural factors. This is equivalent to assuming that parish j's structural factors have no direct impact on the riots in parish i. If this assumption does not hold (e.g., because farm laborers from a deprived parish destroy threshing machines in a wealthier parish nearby), then the coefficient on the spatial lag will confound this effect with contagion.[24] To address this problem, we add a set of variables to equation (1) that account for these effects,

$$\mathbf{W} \times \mathbf{fundamentals} \times \rho, \tag{2}$$

where the row-normalized weight matrix $\mathbf{W}$ has dimension $n \times n$ (so that the sum of entries in any row j adds to 1). The entries corresponding to parishes within 10km of each other are non-zero, while all other entries are set to zero. Importantly, the fact that the weight matrix is row-normalized implies that it averages the value of each of the nine factors across neighboring parishes.[25] The vector ρ has length $k = 9$ and contains the coefficients. Column (4) reports the results: the coefficient on the spatial lag is unaffected and the structural factors of the neighbors are largely insignificant.[26]

[24] To see why, consider a parish j that is within 10km of parish i. Parish j's $\mathbf{fundamentals}_j$ will be correlated with its $\mathbf{riots}_j$, which in turn enter into the specification for $\mathbf{riots}_i$. If $\mathbf{fundamentals}_j$ need to be included in the specification for $\mathbf{riots}_i$ but are omitted, they will be part of the error term, inducing correlation between $\mathbf{riots}_j$ and the error.

[25] We choose to row-normalize our weight matrix because, for example, it is likely that it is the average and not the total wealth across neighboring parishes that matters.

[26] Table A3 in the online appendix reports the estimates for ρ. Only log **area** and log **families in agriculture** have significant coefficients, suggesting that these effects are largely unimportant. Table A4 in the online appendix looks at the interaction between a parish's structural factors and the spatial lag of riots. Petitions, the number of workers in trade and crafts, and the size of a parish have a positive interaction term; this tells us that they helped accelerate the spread of the riots. This is consistent with our interpretation that organizational capacity was a key factor in the Swing riots. Table A5 in the online appendix shows that the results in table 2 are robust to allowing for a 20km neighborhood, removing Kent from the sample (since that is where the riots started) and removing all parishes within 20km of London.

5.3 The relative importance of fundamentals and contagion

The coefficients in equation (1) cannot be interpreted as marginal effects. To see why, consider increasing the value of the riots variable in parish i by one unit. This has an impact on all of i's neighbors, which in turn has an impact on riots in i because i is a neighbor of all of its neighbors. Consequently, in order to estimate the total impact from a one unit increase in the value of element i in **riots** we need to trace the effect through the whole network. To do this, we solve for **riots** in equation (1)

$$\mathbf{riots} = \mathbf{N}\left(\alpha\iota\right) + \mathbf{N}\left(\mathbf{fundamentals} \times \gamma\right) + \mathbf{N}\left(\mathbf{county} \times \delta\right) + \mathbf{Nu}, \tag{3}$$

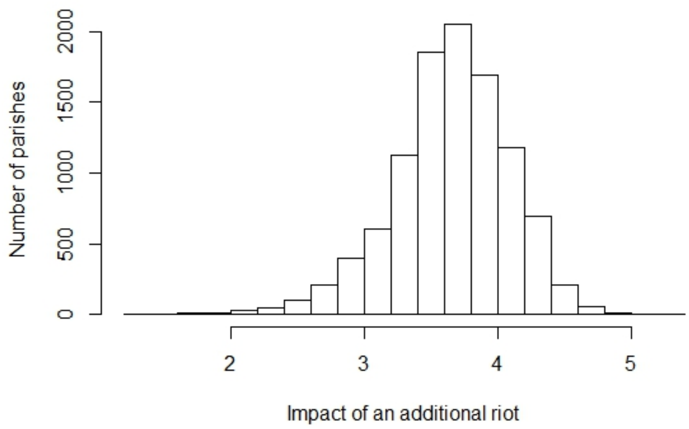
where

$$\mathbf{N} \equiv \left(\mathbf{I} - \beta_1 \mathbf{W}\right)^{-1}. \tag{4}$$

An exogenous riot is a riot that is unexpected from the point of view of this system, and so it enters through a one unit increase in an element of the error vector, say u_i if the unexpected riot happens in parish i. This impacts on riots in parish i directly, and these riots then impact on riots in parish i' neighbors, which in turn impact on riots in their own neighbors (including parish i) and so on. These spatial connections between parishes are captured by the matrix $\mathbf{N}$. In particular, column i captures the impact of a shock to u_i, where $N_{j,i}$ is the total impact on parish j. Therefore, the sum of the elements in column i corresponds to the total impact of an unexpected riot in parish i (a shock to u_i). The size of this impact depends on which parish the shock hits, since connectivity affects its diffusion: different columns have different totals, corresponding to the different impact riots in different parishes have throughout the system. Figure 2 summarizes this information by presenting the distribution of column totals (based on the SHAC coefficients in column (2) of Table 2). The distribution has a mean of 3.65, a median of 3.67, and a standard deviation of 0.44, with a maximum impact of 5.30. To interpret these estimates, consider the average parish: the total impact of an exogenous riot in this parish is 3.65, which can be decomposed into a direct impact of 1 and an impact of 2.65 due to contagion.

How does this compare to the impact of structural factors? The factors in parish i have a direct impact on riots in parish i, but they also indirectly have an impact on riots in other

Figure 2: Distribution of the total increase in riots that results from a one unit increase in an element of $\mathbf{u}$.



Note: The column totals are calculated from the SHAC estimates reported in column (2) of Table 2.

parishes through the feedback process just described. This indirect effect is conceptually contagion originating from parish i's riots, and so it makes sense to compare the direct impact of structural factors to that of the contagion that follows.[27] It is possible then to imagine an exogenous one unit increase in factor k in a parish i and assess its effect on the total number of riots throughout the system. From equation (3), we observe that the term $\mathbf{N}$ (**fundamentals** $\times \gamma$) captures the effect of the factors. The total impact of this one unit increase is then given by $[N_{1,i} + ... + N_{n,i}] \times \gamma_k$; that is, the sum of all the entries in column i of $\mathbf{N}$ captures the total effect (as before), but now we have to multiply that effect by γ_k since this coefficient scales the unit change in that factor. For example, a shock to factor k (e.g., more petitions) in the parish with the average column total will generate a total riot effect equal to $3.65 \times \gamma_k$, of which γ_k is the direct effect and $2.65 \times \gamma_k$ is the result of contagion. In conclusion, the average effect due to contagion is 2.65 times the size of the direct effect of an exogenous change in a structural factor.

[27] In principle, it is possible that structural factors in parish i affect riots in j directly. However, column (4) in Table 2 and Table A3 in the online appendix show that these contextual effects are largely absent.

6 Conclusions

We focus on a historical episode of social unrest, the Swing riots of 1830-1831, to examine the structural factors driving the riots and estimate the importance of these factors relative to contagion. The Swing riots provide an ideal setting in which to address this issue: they allow us to assign structural factors to each specific riot event. We find that the impact of a one unit increase in a structural variable was magnified by a factor of 2.65 by contagion.

Are the lessons from the Swing riots still valuable today in a world where mass and social media play a leading role in episodes of mass protest and social unrest? We believe that they are, especially since recent evidence shows that online media links are largely geographic in nature and between people who live near each other.[28] Furthermore, the potential for structural change to trigger collective violence is as great today as it was in 1830s England. The Swing riots provide us with valuable lessons from history that can help us understand and address these enduring challenges.

References

Aidt, T. S. and R. Franck (2015). Democratization under the threat of revolution: Evidence from the Great Reform Act of 1832. *Econometrica 83*(2), 505–547.

Aidt, T. S. and G. Leon (2016). The democratic window of opportunity: Evidence from riots in sub-Saharan Africa. *Journal of Conflict Resolution 60*(4), 694–717.

Aidt, T. S., G. Leon, and M. Satchell (2018). The social dynamics of collective action: Evidence from the Captain Swing riots, 1830-31.

Albert, W. (1972). *The turnpike road system in England 1663-1840*. Cambridge UK: Cambridge University Press.

Andrews, K. T. and M. Biggs (2006). The dynamics of protest diffusion: Movement organizations, social networks, and news media in the 1960 sit-ins. *American Sociological Review 71*(5), 752–77.

[28]Liben-Nowell et al. (2005) shows that up to 69 percent of listed friends on the LiveJournal online network are geographic in nature.

Andrews, K. T. and M. Biggs (2015). Protest campaigns and movement success: Desegregating the U.S. south in the early 1960s. *American Sociological Review 80*(2), 416–43.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic.

Barker, H. (2000). *Newspapers, politics and English society 1695-1855.* Harlaw, England: Pearson Education.

Bates, A. (1969). *Directory of stage coach services 1836.* New York, NY: Augustus M. Kelley Publishers.

Baudains, P., S. D. Johnson, and A. M. Braithwaite (2013). Geographic patterns of diffusion in the 2011 London riots. *Applied Geography 45*, 211 – 219.

Biggs, M. and S. Knauss (2012). Explaining membership in the British National Party: A multilevel analysis of contact and threat. *European Sociological Review 28*(5), 633–646.

Boyer, G. R. (1990). *An economic history of the English poor law, 1750-1850.* Cambridge, England: Cambridge University Press.

Brooke, S. and N. Ketchley (2018). Social and institutional origins of political Islam. *American Political Science Review.*

Buhaug, H. and K. S. Gledistch (2008). Contagion or confusion? Why conflicts cluster in space. *International Studies Quarterly 52*, 215–233.

Caird, J. (1852). *English agriculture in 1850-51.* London, England: Longman, Brown, Green and Longmans.

Campante, F. R. and D. Chor (2012a). Schooling, political participation, and the economy. *Review of Economics and Statistics 94*(4), 841–859.

Campante, F. R. and D. Chor (2012b). Why was the Arab world poised for revolution? Schooling, economic opportunities, and the Arab Spring. *Journal of Economic Perspectives 26*(2), 167–88.

Caprettini, B. and J. Voth (2017). Rage against the machines: Labor-saving technology and unrest in England, 1830-3. CEPR Discussion Paper 11800, Center for Economic and Policy Research.

Castañeda Dower, P., E. Finkel, S. Gehlbach, and S. Nafziger (2018). Collective action and representation in autocracies: Evidence from Russia's great reforms. *American Political Science Review 112*, 125–147.

Chaney, E. (2013). Revolt on the Nile: Economic shocks, religion, and political power. *Econometrica 81*(5), 2033–2053.

Charlesworth, A. (1979). *Social protest in a rural society: The spatial diffusion of the Captain Swing disturbances of 1830-31.* Norwich, England: University of East Anglia.

Charlesworth, A. (1983). *An atlas of rural protest in Britain 1548-1900.* Philadelphia, Pennsylvania: Pennsylvania University Press.

Clark, P. (2014). *Police and constabulary of England and Wales (eighteenth century until 2014).* London, UK: Peter Clark; Kindle Edition.

Collier, P. and A. Hoeffler (2004). Greed and grievance in civil war. *Oxford Economic Papers 56*(4), 563–595.

Conley, T. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1 – 45.

Dahlum, S. and T. Wig (2017). Educating demonstrators: Education and mass protest in Africa. *Journal of Conflict Resolution*.

Davies, T., H. Fry, A. Wilson, and S. Bishop (2013). A mathematical model of the London riots and their policing. *Scientific Reports 3*.

DiPasquale, D. and E. L. Glaeser (1998). The Los Angeles riot and the economics of urban unrest. *Journal of Urban Economics 43*(1), 52 – 78.

Dorsch, M. T. and P. Maarek (2015). Inefficient predation and political transitions. *European Journal of Political Economy 37*, 37–48.

Enikolopov, R., A. Makarin, and M. Petrova (2016). Social media and protest participation: Evidence from Russia, Unpublished working paper.

Esteban, J., L. Mayoral, and D. Ray (2012, June). Ethnicity and conflict: An empirical study. *American Economic Review 102*(4), 1310–42.

Esteban, J. and D. Ray (2011). A model of ethnic conflict. *Journal of the European Economic Association 9*(3), 496–521.

Fearon, J. and D. Laitin (2003). Ethnicity, insurgency, and civil war. *American Political Science Review 97*(1), 75–90.

Finkel, E., S. Gehlbach, and T. D. Olsen (2015). Does reform prevent rebellion? Evidence from Russia's emancipation of the serfs. *Comparative Political Studies 48*, 984–1019.

Forsberg, E. (2008). Polarization and ethnic conflict in a widened strategic setting. *Journal of Peace Research 45*(2), 283–300.

Gleditsch, K. S. and M. Ward (2006). Diffusion and the international context of democratization. *International Organization 60*, 911–933.

Gonner, E. (1912). *Common land and inclosure.* London, England: Macmilllan.

Granovetter, M. (1978). Threshold models of collective behavior. *American Journal of Sociology 83*(6), 1420–1443.

Griffin, C. J. (2012). *The rural war. Captain Swing and the politics of protest.* Manchester, UK: Manchester University Press.

Hammond, J. L. and B. Hammond (1912). *The Village Labourer 1760-1832.* London, UK: Longman Green & Co.

Hassanpour, N. (2014). Media disruption and revolutionary unrest: Evidence from Mubarak's quasi-experiment. *Political Communication 31*(1), 1–24.

Hays, J. C., A. Kachi, and R. Franzese (2010). A spatial model incorporating dynamic, endogenous network interdependence: a political science application. *Statistical Methodology 7*, 406–428.

Hegre, H. and N. Sambanis (2006). Sensitivity analysis of empirical results on civil war onset. *Journal of Conflict Resolution 50*(4), 508–535. cited By 381.

Hobsbawm, E. and G. Rudé (1973). *Captain Swing.* Harmondsworth: Penguin University Books.

Holland, M. (2005). *Swing unmasked. The agricultural riots of 1830 to 1832 and their wider implications.* Milton Keynes, England: FACHRS Publications.

House of Commons (1831). Index to 83-86th volume. *Journal of the House of Commons.*

House of Commons (1833). Newspaper stamps, England. Return to an order of the honourable House of Commons, dated 24 May 1833; for, an account of the number of stamps issued to each of the provincial newspapers in England, in the year ending on 1st April 1833. *Parliamentary Papers, Accounts and Papers 569.*

Iyer, S. and A. Shrivastava (2016). Religious riots and electoral politics in India, Cambridge Working Papers in Economics 1536.

Jones, D. J. (1982). *Crime, protest, community, and police in nineteenth-century Britain.* London, UK: Routledge and Kegan Paul Books.

Jones, P. (2009, 12). Finding Captain Swing: Protest, parish relations, and the state of the public mind in 1830. *International Review of Social History 54*, 429–458.

Kawalerowicz, J. and M. Biggs (2015). Anarchy in the UK: Economic deprivation, social disorganization, and political grievances in the London riot of 2011. *Social Forces 94*(2), 673–698.

Kelejian, H. and I. Prucha (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate Finance and Economics 17*(1), 99–121.

Kelejian, H. and I. Prucha (2007). HAC estimation in a spatial framework. *Journal of Econometrics 140*(1), 131–154.

Kuran, T. (1989). Sparks and prairie fires: A theory of unanticipated political revolution. *Public Choice 61*(1), 41–74.

Liben-Nowell, D., J. Novak, R. Kumar, P. Raghavan, and A. Tomkins (2005). Geographic routing in social networks. *Proceedings of the National Academy of Sciences of the United States of America 102*(33), 11623–11628.

Little, A. T. (2016). Communication technology and protest. *The Journal of Politics 78*(1), 152–166.

Lohmann, S. (1993). A signalling model of informative and manipulative political action. *American Political Science Review 87*, 319–333.

Lohmann, S. (1994). The dynamics of informational cascades: The Monday demonstrations in Leipzig, East Germany 1989-91. *World Politics 47*, 42–101.

Lotan, G., E. Graeff, M. Ananny, D. Gaffney, I. Pearce, and D. Boyd (2011). The Arab spring the revolutions were tweeted: Information flows during the 2011 Tunisian and Egyptian revolutions. *International Journal of Communication 5*(0).

Marshall, J. (1968). *The old poor law 1795-1934*. London, England: Macmilllan.

McCarthy, J. (1882). *The epoch of reform 1830-1850*. London, UK: Longmans, Green and Co.

Metternich, N., S. Minhas, and M. D. Ward (2016). Firewall? Or wall on fire? A unified framework of conflict contagion and the role of ethnic exclusion. *Journal of Conflict Resolution 61*, 1151–1173.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy 112*(4), 725–753.

Mitra, A. and D. Ray (2014). Implications of an economic theory of conflict: Hindu-Muslim violence in India. *Journal of Political Economy 122*(4), 719–765.

Montalvo, J. and M. Reynal-Querol (2005). Ethnic polarization, potential conflict, and civil wars. *American Economic Review 95*(3), 796–816.

Olson, M. (1965). *The logic of collective action: Public goods and the theory of groups.* Cambridge, MA: Harvard University Press.

Osorio, J. (2015). The contagion of drug violence: Spatiotemporal dynamics of the Mexican war on drugs. *Journal of Conflict Resolution 59*(8), 1403–1432.

Osorio, J., L. I. Schubiger, and M. Weintraub (2017). Vigiliante mobilization and local order: Evidence from Mexico. *Unpublished working paper*.

Owen, W. (1827). *Owen's new book of fairs : being a complete and authentic account of all the fairs in England and Wales, as they have been settled to be held since the alteration of the style.* London, UK: Longman, Rees, Orme.

Piras, G. (2010). SPHET: Spatial models with heteroskedastic innovations in R. *Journal of Statistical Software 35*(1).

Plümper, T. and E. Neumayer (2010). Model specification in the analysis of spatial dependence. *European Journal of Political Research 49*, 418–442.

Sabadello, M. (2012). The role of new media for the democratization processes in the Arab world. In Z. Sereghy, S. Bunk, and B. Preiss (Eds.), *The Arab revolutions: Reflections on the Role of Civil Society, Human Rights and New Media in the Transformation Processes*, pp. 11–20. Stadtschlaining: Austrian Study Center for Peace and Confllict Resolution.

Salehyan, I. and K. S. Gleditsch (2006). Refugees and the spread of civil war. *International Organization 60*, 335–366.

Sambanis, N. (2002). A review of recent advances and future directions in the quantitative literature on civil war. *Defence and Peace Economics 13*(3), 215–243.

Santos Silva, J. M. C. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and Statistics 88*(4), 641–658.

Scacco, A. (2008). Who riots? Explaining individual participation in ethnic violence, Unpublished working paper.

Scacco, A. L. (2016). *Anatomy of a Riot: Why Ordinary People Participate in Ethnic Violence*. Book manuscript.

Stark, M. J. A., W. J. Raine, S. L. Burbeck, and K. K. Davison (1974). Some empirical patterns in a riot process. *American Sociological Review 39*(6), 865–876.

Tate, W. (1978). *A Domesday of English enclosure acts and awards.* Reading, UK: The Library, University of Reading.

Thompson, E. P. (1963). *The making of the English working class.* London UK: Victor Gollancz Ltd, Vintage Books.

Tilly, C. (1995). *Popular contention in Great Britain, 1758-1834.* Cambridge, MA: Harvard University Press.

Urdal, H. (2006). A clash of generations? Youth bulges and political violence. *International Studies Quarterly 50*(3), 607–629.

War Office (1830). *A List of the Officers of the Army and of the Corps of Royal Marines, Full, Retired and half-pay.* London, UK: His Majesty's Stationary Office.

Well, R. (1997). Mr William Cobbett, Captain Swing, and King William IV. *Agricultural History Review 45*, 34–48.

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the Rwandan genocide. *The Quarterly Journal of Economics 129*(4), 1947–1994.

A Online appendix (not for publication)

This appendix provides definitions of all the variables used in the analysis and lists the sources used to construct them. It also presents summary stats, the additional robustness checks referred to in the main text, and a number of maps.

A.1 GIS datasets

The following GIS datasets have been used to construct the dataset used in the estimations:

1. Wrigley, E.A., Shaw-Taylor, L., and Newton, G., (2010). 1831 Census Report of England: County Parish Occupations. This dataset was produced with funding from the ESRC, The Occupational Structure of Nineteenth Century Britain, RES 000-23-1579. For details of the dataset Wrigley, E.A., The Early English Censuses, British Academy, Records of Economic and Social History (Oxford, 2011)

2. Satchell, A.E.M., Boothman, L., Shaw-Taylor, L., and Bogart, D., (2016). Parliamentary Enclosure Dataset. This dataset was produced with funding from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093.

3. Shaw-Taylor, Broad, J., and Newton, G., (2016). The 1815 Return of Real Property for England and Wales. This dataset was produced with funding from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093.

4. Shaw-Taylor, L., Satchell, A.E.M., and Newton, G., (2016). The Cambridge Group England and Wales Towns Database. This dataset was produced with funding from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093.

5. Satchell, A.E.M., Shaw-Taylor, L., and Potter, E., (2016). The Cambridge Group England and Wales Town Points Dataset. This dataset was produced with funding

from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093.

6. Satchell, A.E.M, Newton, G., Bogart, D., and Shaw-Taylor, L., (2014). Bates, Directory of stage coach services 1836. This dataset and associated shapefile were created from Bates, A., Directory of stage coach services 1836 (1969). This dataset was produced with funding from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093, with funding from the Leverhulme Trust.

7. Satchell, A.E.M., Kitson, P.M.K., Newton, G.H., Shaw-Taylor, L., and Wrigley E.A., (2016). 1851 England and Wales census parishes, townships and places (2016). This dataset was created with funding from the ESRC (RES-000-23-1579), the Leverhulme Trust and the British Academy. A description of the dataset can be found in Satchell, A.E.M., England and Wales census parishes, townships and places: documentation (2016, 2006) available at: http://www.geog.cam.ac.uk/research/projects /occupations/datasets/documentation.html.

8. Satchell, A.E.M, Shaw-Taylor, L., and Wrigley E.A., (2016). 1831 England and Wales ancient counties GIS. This dataset was created with funding from the ESRC (RES-000-23-1579), the Leverhulme Trust and the British Academy. A description of the dataset can be found in Satchell, A.E.M., England and Wales ancient counties 1831 documentation (2016, 2006) available at: http://www.geog.cam.ac.uk/research /projects/occupations/datasets/documentation.html

A.2 Definition of variables and sources

We use the following notation in the definitions of the variables below: (i) $i = 1, 2, ..., n$ is the index for parishes where n is the total number of parishes; (ii) N at the end of a variable name refers to the "neighborhood" of a parish defined as parishes within a radius of 10km from its centroid. We use the following variables:

- **riots** is an $n \times 1$ vector where element i is the total number of riots in parish i between Monday, 28th June 1830 and Sunday, 3rd April 1831. Source: Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{W} \times$ **riots** is an $n \times 1$ vector and $\mathbf{W}$ is a $n \times n$ row-normalized weight matrix with non-zero entries corresponding to parishes with centroids within 10km of each other, and all other entries set to 0. Parish i is not considered to be its own neighbor. The variable captures the average riots in a 10km neighborhood of a parish. Source: constructed from Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- Log **area** is an $n \times 1$ vector where element i is the natural logarithm of the area in English statute acres of parish i. Calculated from Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- Log **population** is an $n \times 1$ vector where element i is the natural logarithm of the total number of inhabitants in parish i in 1831 (in 1000s). Source: Census of Great Britain, 1831. Wrigley, Shaw-Taylor and Newton (2010).

- **High wage, cereal** is an $n \times 1$ vector where element i equals one if parish i is located in the high wage cereal growing regions of England, i.e. the northeast of England. Source: Caird (1852).

- **Low wage, cereal** is an $n \times 1$ vector where element i equals one if parish i is located in the low wage cereal growing regions of England, i.e. in the south-east and East Anglia. Source: Caird (1852).

- **Low wage, dairy** is an $n \times 1$ vector where element i equals one if parish i is located in the low wage dairy farming regions of England, i.e. in Cornwall, the southwest of England, or parts of Wales and the Midlands. Source: Caird (1852).

- **High wage, dairy** is an $n \times 1$ vector where element i equals one if parish i is located in the high wage dairy farming regions of England, i.e. the northwest of England. This is the omitted category in the regression analysis. Source: Caird (1852).

- Log **families in agriculture** is an $n \times 1$ vector where element i is the natural logarithm of the number of families chiefly employed in agriculture in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- Log **farmers** is an $n \times 1$ vector where element i is the natural logarithm of the number of male agricultural occupiers (tenant farmers or landowners) aged 20 or over in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- Log **manufacturing workers** is an $n \times 1$ vector where element i is the natural logarithm of the number of males aged 20 or over employed in manufacturing or in making manufacturing machinery in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- Log **traders and craftmen** is an $n \times 1$ vector where element i is the natural logarithm of the number of males aged 20 or over employed in trade or in handicraft as masters or workmen in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- Log **professionals** is an $n \times 1$ vector where element i is the natural logarithm of the number of males aged 20 or over classified as capitalists, bankers, professionals and other educated men in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- Log **males** is an $n \times 1$ vector where element i is the natural logarithm of the number of males aged 20 or over in parish i. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- **enclosed before 1830** is an $n \times 1$ vector where element i is equal to one if parish i was affected by any enclosure acts dated 1830 or earlier, and 0 otherwise. Source: Tate (1978); Satchell, Boothman, Shaw-Taylor, and Bogart (2016).

- Log **wealth** is an $n \times 1$ vector where element i is the natural logarithm of the annual value of real property in parish i (as assessed in April 1815). Source: Census of Great Britain 1831. (1831 (348) Population. Comparative account of the population of Great Britain in the years 1801, 1811, 1821, and 1831) and Shaw-Taylor, Broad, and Newton (2016).

- **marketN** is an $n \times 1$ vector where element i is equal to one if parish i was located within a 10km radius of a weekly or bi-weekly market. The information on markets is from Owen (1827), which contains a directory of regular markets in England and Wales in 1827. Geo-referenced using Shaw-Taylor, Satchell, and Newton (2016) and Satchel, Shaw-Taylor, and Potter, (2016).

- **coachstopN** is an $n \times 1$ vector where element i is equal to one if parish i was within 10km of a stop on the stage coach network. The information on the location of the coach stops comes from Bates (1969), which contains a timetable and a directory for the stage coach services in 1836. Geo-referenced using Satchell, Newton, Bogart, and Shaw-Taylor (2014).

- Log **petitions** is an $n \times 1$ vector where element i is the natural logarithm of the number of petitions originating from parish i and submitted to the House of Commons between 1828 and 1831. The petitions were related to abolition of slavery, parliamentary reform, and rights for Catholics (Catholic relief). The House of Commons (1831) reports a list of petitions with information on content and on who had written each of them. We geo-referenced the locations from which the petitions originated and matched this to the parish GIS using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- **newspaperN** is an $n \times 1$ vector where element i is equal to one if parish i is located within a 10km radius of a town with a local or regional newspaper, and zero otherwise. House of Commons (1833) enables us to deduce the geography of the local and national newspapers. This return to the House of Commons from 1833 reports the stamp duties paid by each newspaper published in England. From the names of the newspapers, we infer the location where the 130 local and regional newspapers were published. We assume that county newspapers were published in the county seat. Source: House of Commons (1833). Outside of London, all 130 local or regional newspapers were weeklies. In London there were 12 dailies (with The Times being by far the largest), seven newspapers were published three times a week, one twice a week and 37 once a week.

- Log **distance to garrison** is an $n \times 1$ vector where element i is the natural logarithm of the "as the crow flies" distance in kilometers from a parish's centroid to the nearest army or navy garrison. Source: War Office (1830).

- **policeN** is an $n \times 1$ vector where element i is equal to one if parish i is located within a 10km radius of a town with a police force. Source: Clark (2014).

A.3 Descriptive statistics and additional results

Table A1 shows the different types of Swing riot events in our dataset.

Table A1: The Swing riots, by type.

Riot type	Number
Arson	1306
Attempted arson	54
Machine breaking (Threshing machines)	538
Machine breaking (other agricultural machinery)	47
Machine breaking (Industrial machines)	35
Sending anonymous threatening letters	270
Robbery	254
Wage riot	289
Tithe riot	67
Rescue of prisoners	102
Damage to crops, fences, etc.	32
Animal maiming	74

Source: Holland (2005).

One concern is that riots near newspapers may have been more likely to be reported. In this case we would expect that proximity to newspapers would predict riots. This is not the case; a regression of total number of riots on distance to the nearest newspaper generates a small coefficient and a p-value of 0.32. In order to assess whether the newspapers systematically under-reported riots in distant rural areas, we plot two distributions in Figure 3: the first is a distribution of distances to the nearest newspaper for all parishes that experienced at least one riot, while the second is of distances to nearest newspaper for parishes that experienced no riots. Under a null hypothesis of under-reporting, we would expect the first distribution to be much closer to the vertical axis, as this would show that indeed the riots are from an unrepresentative sample of parishes (unrepresentative in terms of distance to nearest newspaper). The fact that both distributions are so similar leads us to reject this null hypothesis.[29]

Figure 3: Distribution of distances to newspapers

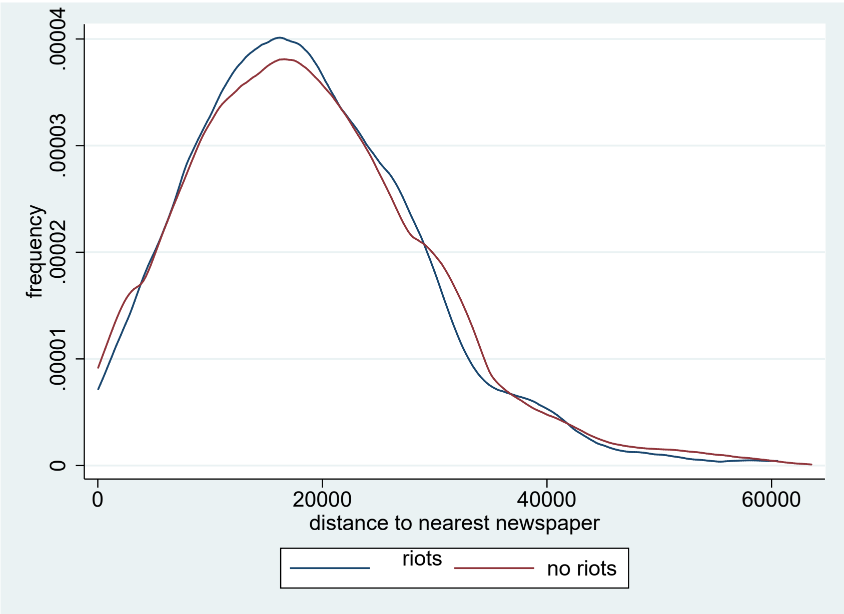


Table A2 shows the summary statistics for the main variables used in our estimation.

[29]Naturally, it is possible that in the absence of under-reporting we would find the first distribution to the right of the second, and that the under-reporting simply causes them to become closer than they would be otherwise. This seems unlikely, especially given that the distributions end up being very similar.

Table A2: Summary statistics

	N	mean	sd	min	max
Riots	10,335	0.22	0.91	0	20
Log **area**	10,335	2.19	0.90	0.00074	6.09
Log **population**	10,317	6.11	1.24	0	12.0
High wage, cereal	10,335	0.10	0.30	0	1
Low wage, dairy	10,335	0.34	0.47	0	1
Low wage, cereal	10,335	0.41	0.49	0	1
Log **families in agriculture**	10,317	3.73	1.14	0	6.77
Log **farmers**	10,317	2.47	1.01	0	5.66
Log **manufacturing workers**	10,317	0.50	1.28	0	9.38
Log **trader and craftmen**	10,317	3.02	1.58	0	9.86
Log **professionals**	10,317	1.37	1.31	0	8.60
Log **males**	10,317	5.42	1.21	0	11.2
Enclosed before 1830	10,335	0.36	0.48	0	1
Log **wealth**	9,492	1.99	0.54	0	5.76
MarketN	10,335	0.92	0.27	0	1
CoachstopN	10,335	0.63	0.48	0	1
Log **petitions**	10,335	0.25	0.51	0	4.06
NewspaperN	10,335	0.22	0.41	0	1
Log **distance to garrison**	10,335	10.7	0.88	3.51	11.9
PoliceN	10,335	0.37	0.48	0	1
W $\times$ **riots**	10,335	0.21	0.36	0	4.72

Notes: The variables names refer to vectors. For each vector, N is the number of elements with non-empty values, mean is the average value of the non-empty elements, the standard deviation is calculated using the value of non-empty elements, and min and max refer to the minimum and maximum values taken by the non-empty elements.

Table A3: Cross-section estimates: the contextual effects

VARIABLES	(1) **riots**	(2) **riots**
W × **riots**	0.63	0.52
	(0.048)***	(0.068)***
W× Log **area**	-0.11	-0.66
	(0.030)***	(0.19)***
W× Log **population**	0.32	1.07
	(0.25)	(1.56)
W× **Low wage, cereal**	0.15	0.43
	(0.15)	(0.52)
W× Log **families in agriculture**	0.058	0.58
	(0.021)***	(0.16)***
W× Log **traders and craftmen**	0.029	0.074
	(0.034)	(0.26)
W× Log **professionals**	-0.040	-0.15
	(0.034)	(0.20)
W× Log **males**	-0.37	-1.39
	(0.24)	(1.71)
W× Log **petitions**	-0.089	-0.27
	(0.064)	(0.34)
W× **policeN**	-0.077	-0.075
	(0.057)	(0.22)
Log **area**	0.12	0.57
	(0.021)***	(0.074)***
Log **population**	-0.015	1.12
	(0.064)	(0.68)*
Low wage, cereal	0.10	0.37
	(0.13)	(0.46)
Log **families in agriculture**	0.0076	0.031
	(0.014)	(0.067)
Log **traders and craftmen**	0.049	0.19
	(0.015)***	(0.085)**
Log **professionals**	0.041	-0.015
	(0.012)***	(0.059)
Log **males**	-0.010	-0.95
	(0.073)	(0.68)
Log **petitions**	0.096	0.13
	(0.035)***	(0.085)
policeN	0.057	0.16
	(0.042)	(0.13)
Observations	10,309	10,309
R-squared	0.193	
Dummies	County	County
Standard errors	Conley	Cluster by par
Estimation	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. We use the notation $\mathbf{W} \times \mathbf{fundamental_k}$ to indicate the contextual effect of fundamental k. The weight matrix **W** is row-normalized so that the sum of entries in any row j adds to 1. This means that it is the average of each of the nine fundamentals in the 10km neighborhood of a parish. In column (1) the standard errors are corrected for serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). Column (2) reports results from a Poisson estimator; the standard errors are clustered at the county level.

Table A4: Cross-section estimates: interactions

VARIABLES	(1) **riots**	(2) **riots**
D(Log **area**) $\times$**W** $\times$ **riots**	0.023	0.0086
	(0.0038)***	(0.0042)**
D(Log **population**) $\times$**W** $\times$ **riots**	0.00079	0.076
	(0.0098)	(0.020)***
D(Log **families in agriculture**) $\times$**W** $\times$ **riots**	0.0031	0.0028
	(0.0036)	(0.0052)
D(**Low wage, cereal**) $\times$**W** $\times$ **riots**	0.0076	-0.022
	(0.0040)*	(0.0097)**
D(Log **traders and craftmen**) $\times$**W** $\times$ **riots**	0.011	-0.0048
	(0.0025)***	(0.0040)
D(Log **professionals**) $\times$**W** $\times$ **riots**	0.0039	-0.0013
	(0.0026)	(0.0035)
D(Log **males**) $\times$**W** $\times$ **riots**	-0.017	-0.080
	(0.011)	(0.024)***
D(Log **petitions**) $\times$**W** $\times$ **riots**	0.017	0.00059
	(0.0043)***	(0.0042)
D(**policeN**) $\times$**W** $\times$ **riots**	0.0044	-0.00043
	(0.0049)	(0.0044)
Log **area**	0.016	0.44
	(0.016)	(0.079)***
Log **population**	0.097	-0.046
	(0.075)	(0.74)
Low wage, cereal	0.11	0.82
	(0.080)	(0.24)***
Log **families in agriculture**	-0.028	0.072
	(0.020)	(0.078)
Log **traders and craftmen**	-0.018	0.36
	(0.011)*	(0.096)***
Log **professionals**	0.018	0.0071
	(0.015)	(0.066)
Log **males**	-0.024	0.071
	(0.075)	(0.77)
Log **petitions**	0.014	0.13
	(0.025)	(0.10)
policeN	-0.026	0.072
	(0.029)	(0.12)
Observations	10,317	10,317
R-squared	0.242	
County dummies	YES	YES
Standard errors	Conley	Cluster by par
Estimation	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. $\mathbf{D}(\mathbf{x})$ refers to an $n \times n$ diagonal matrix where element (i, i) equals the value of structural factor x in parish i. The expression $\mathbf{D}(\mathbf{x}) \times \mathbf{W} \times$ **riots** refers to the interaction between each parish's fundamental x and the spatial lag of riots. In column (1) the standard errors are corrected for serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). Column (2) reports results from a Poisson estimator; the standard errors are clustered at the county level.

Table A5: Cross-section estimates: robustness

VARIABLES	(1) **riots**	(2) **riots**	(3) **riots**
W $\times$ **riots**	1.14	0.76	0.71
	(0.054)***	(0.051)***	(0.059)***
Log **area**	0.11	0.08	0.11
	(0.044)**	(0.031)***	(0.042)**
Log **population**	0.04	0.04	0.05
	(0.048)	(0.042)	(0.049)
Low wage, cereal	0.08	0.15	0.17
	(0.024)***	(0.028)***	(0.028)***
Log **families in agriculture**	0.02	0.01	0.03
	(0.009)**	(0.009)	(0.008)***
Log **traders and craftmen**	0.06	0.06	0.06
	(0.014)***	(0.012)***	(0.013)***
Log **professionals**	0.043	0.03	0.04
	(0.010)***	(0.005)***	(0.011)***
Log **males**	-0.09	-0.09	-0.09
	(0.059)	(0.051)*	(0.059)
Log **petitions**	0.09	0.10	0.10
	(0.026)***	(0.025)***	(0.029)***
policeN	0.01	0.01	0.02
	(0.009)	(0.008)	(0.013)
Observations	10,309	9,884	10,038
County dummies	YES	YES	YES
Standard errors	Spatial	Spatial	Spatial
Estimation	SHAC	SHAC	SHAC
Note	20km neighborhood	No Kent	excl $<$ 20km London

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. The unit of observation is the parish, and element i in the vector **riots** equals the total number of riots in parish i during the 40 weeks of the uprising. For a parish i, in column (1) **W** $\times$ **riots** refers to the average number of riots across parishes within 20km of its centroid (excluding riots that happened in i itself). In columns (2) and (3) it refers to the 10km neighborhood, but excludes Kent and parishes near London, respectively. The structural factors we include are those that were statistically significant in at least one of the specifications reported in Table 1. The SHAC estimator used to estimate the coefficients is implemented with the sphet package in R (see Piras (2010)), using a row-normalized weight matrix where parishes within 10km (Euclidean distance) are considered neighbors. The standard errors reported in these columns are robust to heteroskedasticity and spatial correlation.

A.4 Maps

Figure M1: Map of the four agricultural regions of England and Wales (Caird)

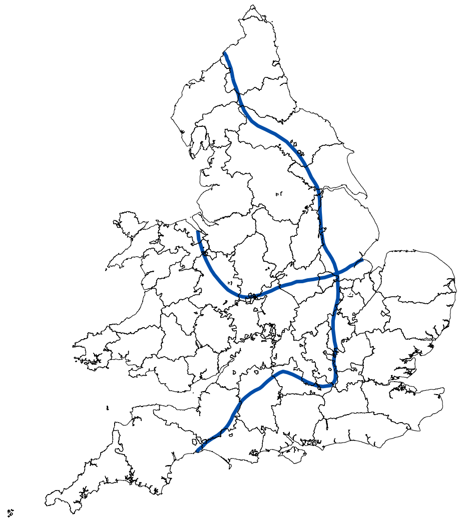


Figure M2: Map of the location of markets and fairs

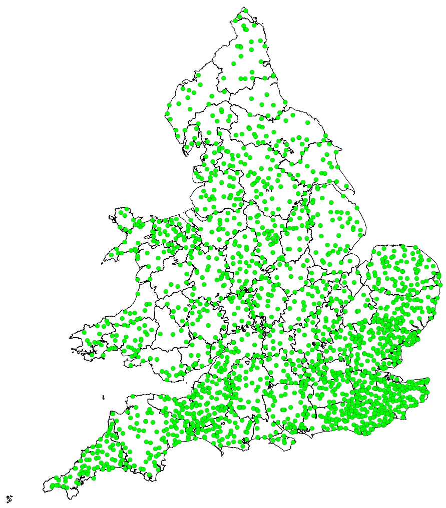
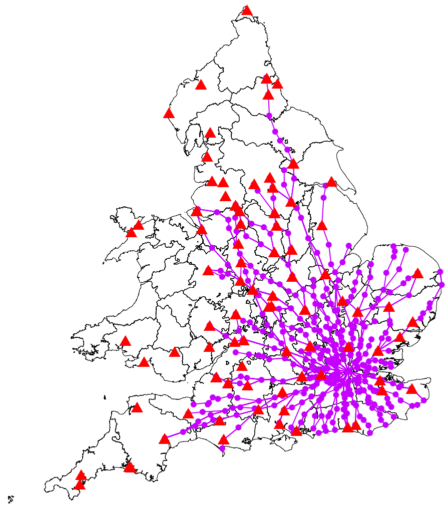
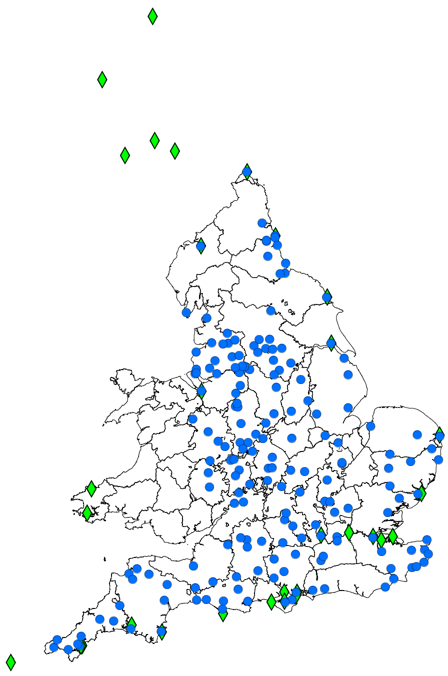


Figure M3: Map of the location of coach stops and regional newspapers



Notes: Each purple dot represents a coach stop and each red triangle represents a town with a newspaper.

Figure M4: Map of the location of police stations and garrisons



Notes: Each green diamond represents a garrison and each blue dot represents a police station.

Figure M5: Map of the locations from which petitions were sent