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The Social Dynamics of Collective Action: Evidence from the Diffusion of the Swing Riots, 1830-31*

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Abstract

Social unrest often begins suddenly and spreads quickly. What is the information that drives its diffusion? How is this information transmitted? And who responds to this information? We present a general framework that emphasizes three aspects of the diffusion process: the networks through which information travels, whether information about repression affects participation, and the role of organizers. We use this framework to derive empirical hypotheses that we test in the context of the English Swing riots of 1830-31. This was the foundational case in the study of unrest in social history, and our identification strategy relies on spatiotemporal variation particular to this historical period. We find that diffusion was significant and that information about the riots traveled through personal and trade networks, but not through transport or mass media networks. This information was not about repression; and local organizers played an important role in the diffusion of the riots.

Keywords: Social unrest, riots, diffusion, networks, Captain Swing.

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1 Introduction

Riots and other forms of social unrest often begin suddenly and spread quickly; recent examples include the 1992 Los Angeles riots, the 2005 French riots and the 2011 London riots. How do people overcome their collective action problem, turning what is initially an isolated incident into a wave of unrest? The literature considers two main explanations for why social unrest spreads: the first emphasizes *fundamentals* including socio-economic factors like poverty, unemployment and ethnicity, while the second emphasizes *diffusion*.[1] This paper focuses on the diffusion of social unrest. What is the type of information that drives this process? How is this information transmitted? And who responds to this information? Answering these questions will shed light on a process that the literature often treats as a black box.

We begin with a theoretical framework that builds on the theory of technology diffusion developed in Rogers (1995). In his theory, innovations spread to potential adopters through information networks. We adapt this idea to the context of social unrest: an initial incident of unrest diffuses when other individuals decide to participate because of information they have received about it. We also highlight three specific features that are key in this setting. The first is the specific networks through which information can spread; we consider four that feature prominently in the qualitative literature: personal, trade, transport and mass media networks. The second relates to the type of information that is transmitted through these networks, and we distinguish between information that inspires others to participate and information that helps individuals evaluate the costs and benefits of participation. The third relates to whether the response to this information comes spontaneously from individual participants or is mediated by organizers.

We use this framework to produce hypotheses about the mechanisms behind the diffusion of social unrest, which we then test in the context of the foundational case in the study of unrest in social history: the Swing riots of 1830-1831. The Swing riots were the largest wave of unrest in 19th century England; over the course of 40 weeks, thousands of farm

[1] Examples of the first literature include Finkel, Gehlbach, and Olsen (2015), Kawalerowicz and Biggs (2015), Aidt and Leon (2016), Scacco (2016), and Castañeda Dower et al. (2018); while examples of the second include Granovetter (1978), Kuran (1989), Lohmann (1994, 1993), Andrews and Biggs (2006), and Myers (2000a, 2010).

laborers rioted across the country, motivated by an economic crisis that they blamed on local farmers and officials.[2] Our analysis relies on a dataset that includes nearly 3,000 Swing-related incidents, and records both the parish and the location where each incident happened. To put this data together we collected, digitized and geocoded the location and date of each Swing incident, the location and date of fairs, the location where newspapers were printed, the location of stops in the coach network, the number of petitions sent to parliament from each parish, and the number, location and date of riot-related arrests.

The main challenge in estimating diffusion is the reverse Galton problem (Buhaug and Gledistch 2008): what appears to be diffusion may instead be the result of unit attributes that are spatially clustered. The Swing riots help us address this identification problem. By current standards, the riots spread in slow motion, with the process allowed to develop more or less unchecked for weeks before the national authorities intervened. However, the riots still spread fast enough for all other factors, including the socio-economic fundamentals, to remain largely unchanged in the relevant time frame. Consequently, we can control for these fundamentals by including parish fixed effects, week effects and location-specific time trends. This means that the only variable that changes in the short-run is the number of riots in the neighborhood of a parish, which allows us to estimate diffusion.

We find that diffusion through personal networks was substantial: one riot in the neighborhood increased the incidence of riots in a parish by more than 50%. Furthermore, a riot in a well-connected parish at the right time could generate more than one additional riot in its neighborhood the following week, accounting for the explosive way in which the riots spread. We also find that trade networks facilitated the spread of the riots; this is a contribution to a growing literature that explores the relationship between trade and conflict (e.g. Jha 2013). However, we find no evidence that transport networks or the media affected diffusion; this differs from the more common finding that they are central to the spread of unrest (e.g. Myers 2000a; Crabtree, Darmofal, and Kern 2015; Ketchley and Brooke 2018; Cunningham and Phillips 2007).

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[2] We define social unrest as instances of small-scale violence where individuals disturb the public peace for a common purpose. The historiographical literature on the Swing riots refers to these incidents as riots, and for consistency with that literature we follow its terminology. See Wilkinson (2009) for an excellent discussion of the various definitions of the word “riots”.

The second element of the theory relates to the type of information that facilitates or hinders diffusion. We consider two possibilities: the information is about the unrest itself and provides inspiration, or it is about the authorities' response to it. To test whether the information was about the authorities' response to the Swing riots, we look at the relationship between arrests and future rioting. We find that arrests reduced future rioting in the parish where they happened, but they did not affect rioting in neighboring parishes. We interpret this as evidence that cost-benefit calculations were important in the decision to participate, but did not affect diffusion. The third element relates to the question of organization. We consider two possibilities that reflect the debate between those who conceptualize unrest as spontaneous or emergent phenomena (e.g. Epstein 2002; Hobsbawm and Rudé 1973) and those who see them as organized by plotters and activists (e.g. Wilkinson 2004; Charlesworth 1979). Our findings suggest that local activists played an important part in the diffusion of the Swing riots.

Social scientists increasingly recognize that riots and other forms of social unrest cannot be thought of as a set of independent incidents caused by underlying socio-economic fundamentals. The incidents are linked together: individuals participate because others do (e.g., Biggs 2003). Our paper contributes to this new literature in a number of important ways. First, we show how time variation can be used to distinguish between spatially clustered fundamentals and diffusion. This helps address a shortcoming of much of the research on diffusion, including work on riots in the United States (Myers 2000a, 2010) and in the UK (Baudains, Johnson, and Braithwaite 2013; Davies et al. 2013), which cannot establish whether the spatial clustering of unrest is due to common socio-economic factors or to diffusion. Second, our theoretical framework allows us to examine three key aspects of the diffusion process – the information networks, the type of information transmitted, and the organization of collective action – and in doing so shed light on a process that the literature usually treats as a black box.

We focus on a historical case because engaging with these questions using more recent data would present a number of insurmountable challenges. Today most people hear about an incident of social unrest soon after it starts: information travels very quickly, and as a result the unrest typically diffuses over the course of a day or two. This means that there is limited temporal variation, making it difficult to distinguish between the effect of spatially clustered fundamentals and diffusion. Diffusion is an important feature of many social processes, and understanding why and how it happens represents a contribution to the broader literature on contentious politics, including strikes (Biggs 2003), sit-ins (Andrews and Biggs 2006, 2015) and protests (Crabtree, Darmofal, and Kern 2015).

2 Theoretical framework

Our theoretical argument builds on the theory of technology diffusion developed by Rogers (1995), and in particular the idea that information about an innovation is spread through networks that are determined by social structure. Adapted to our setting, the diffusion process starts when instigators engage in social unrest and information about this incident reaches other individuals in their network. These individuals then decide whether to participate, and as in Granovetter (1978) and Kuran (1989), their decision depends on whether the information they have received tips them over their participation thresholds. That is, the nature of the information and who receives it are important factors in determining whether social unrest spreads. If these individuals decide to participate in the unrest, there is another incident and information about it then travels to other potential participants.[3] In this way social unrest can spread over a large area in a relatively short amount of time.

In order to fully understand diffusion, we need to examine this process in detail. We emphasize three key elements. First, information about the unrest and its consequences must reach potential participants, and this happens through *information networks*. As emphasized by Strang and Soule (1998), the structure of these networks shapes the diffusion process. We examine four networks and the way in which they could have spread information about the unrest. Second, the nature of the *information transmitted* is important because that is what potentially pushes individuals over their participation thresholds. Third, participants may solve their collective action problem spontaneously or with the help of local activists; this is closely linked to the question of who receives and responds to the information: the possible organizers of the unrest or the individuals who participate in it.

[3] We focus on the process of diffusion conditional on the first incident of social unrest having taken place. Our theory does not explain how that initial incident starts, in the same way that the theory of technology diffusion does not explain technological innovation.

2.1 The information networks

We consider four networks that can shape the diffusion process: personal, trade, transport, and mass media networks. *Personal networks* of individuals who live near each other play an important role in many accounts of diffusion in contentious politics, including those of the Detroit riots of 1967 (Singer, Osborne, and Geschwender 1970), the Paris Commune in 1871 (Gould 1991) and the US civil rights movement in the 1960s (Morris 1981). Personal ties allow individuals to exchange information about the unrest face-to-face, and since these individuals are closely connected, they are more likely to influence each other. In this way, social unrest spreads locally.

Hypothesis 1 *(Personal networks) Locations experience diffusion from incidents of social unrest in nearby locations.*

Other networks are likely to play a role too. Many scholars have emphasized the importance of trade in the diffusion of knowledge and technology (e.g., Huberman and Meissner 2010; Moser 2013), and we conjecture that social unrest may spread along *trade networks.* Individuals who meet to trade will often exchange information about recent events, including incidents of social unrest. This is consistent with the idea that the exchange of information during market transactions can facilitate the spread of riots (Bohstedt and Williams 1988), and with Rudé (1964)'s observation that in the 18th and 19th centuries, the network of market towns served as relay stations in the diffusion of riots in England and France.

Hypothesis 2 *(Trade networks) Locations near trade hubs experience more diffusion than other locations.*

Transport networks also connect individuals and create hubs where information can be exchanged, potentially facilitating diffusion. For example, when describing the spread of the French Corn Riots of 1775, Rudé (1964, p. 24) says that "the riots followed the course of [these] rivers or crossed them at strategic points, spreading from one market town to the next." There is quantitative evidence that transport networks have played a role in other settings too; for example, Brooke and Ketchley (2018) show that the propagation of the Muslim Brotherhood in Egypt in the period leading to the Second World War was facilitated by the rail network, while Cunningham and Phillips (2007) show that state routes

Figure 1: Hypotheses

Category	Hypotheses	Operationalization in the context of the Swing riots
Personal networks	H1: Locations experience diffusion from incidents of social unrest in nearby locations	Parishes within 10km of locations with riots at *t-1* should experience more riots.
Trade networks	H2: Locations near trade hubs experience more diffusion than other locations	Parishes within 10km of a fair at *t-1* should experience more riots. This effect should be greater if there were riots near the fair at *t-1*.
Transport networks	H3: Locations near transport hubs experience more diffusion than other locations	Parishes near a coach stop should experience more diffusion from riots in a 10km neighborhood.
Mass media	H4: Locations with better access to the media experience more diffusion than other locations	Parishes near a newspaper should experience more diffusion from riots in a 10km neighborhood.
Repression	H5: Social unrest that is not repressed diffuses; social unrest that is repressed does not	Parishes with riots in a 10km neighborhood at *t-1* that resulted in arrests should experience fewer riots at *t* Parishes with riots in a 10km neighborhood at *t-1* that did not result in arrests should experience more riots at *t*
Organizers	H6: Locations with more organizers will experience more diffusion	Parishes that sent more petitions should experience more diffusion from riots in a 10km neighborhood

and highways aided in the expansion of the Ku Klux Klan in North Carolina. Consequently, proximity to the transport network should make an area more likely to experience diffusion.

Hypothesis 3 *(Transport networks) Locations near transport hubs experience more diffusion than other locations.*

While personal, trade and transport networks connect individuals physically in a way that allows them to exchange information face-to-face, information can be communicated impersonally to a large group of people through the mass media. The media can therefore play a very large role in driving diffusion. Recent quantitative research has found the media to have been of importance in triggering and sustaining unrest in a large variety of contexts, including the United States in the 1960s (Myers 2000a; Andrews and Biggs 2006), Germany before the fall of the Berlin Wall (Crabtree, Darmofal, and Kern 2015), Russia in the aftermath of the 2011 election (Enikolopov, Makarin, and Petrova 2020) and Egypt during the Arab Spring (Hassanpour 2014).

Hypothesis 4 *(Mass media) Locations with better access to the media experience more diffusion than other locations.*

2.2 The information transmitted

What is the type of information that is transmitted through the networks and causes diffusion? This information is important because it determines whether individuals are pushed over their participation thresholds (Granovetter 1978). We argue that the information could inspire potential participants, for example by providing ideas about new elements in the repertoire (Biggs 2003; Tilly 1988; McAdam, Tarrow, and Tilly 2001; Tarrow 2011). Alternatively, it could help potential participants evaluate the costs and benefits of participation: they may learn that it is possible to obtain concessions from the authorities or that law enforcement is ineffective; this increases the benefit and lowers the cost of participation, fueling diffusion. Consequently, we conjecture that information about repression will play an important role in whether individuals decide to participate.[4]

Hypothesis 5 *Social unrest that is not repressed diffuses; social unrest that is repressed does not.*

2.3 The organizers of collective action

The response to the information that is transmitted through the four networks can be either spontaneous or organized. If spontaneous, individuals mobilize without organization; there are a number of recent cases where this has happened, including the 2011 London riots (Morrell et al. 2011). However, social unrest can also be organized, in which case there is typically a complementary relationship between the organizers (the "brains") and the participants (the "muscle"), where the first are the political entrepreneurs who solve the collective action problem (Olson 1965) and the second are the mass of individuals who participate. There are well-known instances in which political leaders strategically orchestrate riots in order to further their political objectives (e.g. Wilkinson 2004). Our hypothesis is that organizers play an important role in the diffusion process (against the alternative that they do not).

Hypothesis 6 *Locations with more organizers will experience more diffusion.*

Figure 1 summarizes our hypotheses and indicates how they will be operationalized using data from the Swing riots. In the next section, we discuss this operationalization in more detail.

[4] Concessions could be important too; for example, Conell and Cohn (1995) show that coal mining strikes in France spread more strongly when they are successful. Unfortunately we do not have data to test hypotheses about concessions.

3 Data and historical background

We evaluate these hypotheses using data from the Swing riots, the largest rural uprising in 19th century England. The data on the riots were originally compiled by Hobsbawm and Rudé (1973, Appendix II) and substantially extended by Holland (2005). Their primary sources were London-based periodicals, Home Office documents, archival reports and newspapers. The data record the location of 2,818 riots, the day of the riot, and for a subset of them a short characterization of their nature. From Holland (2005, Appendix I) we have the names of 1,673 individuals who were arrested and tried for participating in the riots, and this allows us to identify 484 riots that resulted in at least one arrest. For some of the riots we also have information on the number of participants (Horn and Tilly 1988). The riot data should be a nearly complete record of the riots that were reported, and although it is likely that some incidents were missed, there is no evidence of systematic under-reporting.[5] We geo-referenced each riot and aggregated the daily observations by week. The unit of analysis is the parish-week; we have data for the 10,335 parishes in England for the 40 weeks between June 28 1830 and April 3 1831. Social historians date the start of the Swing Riots to early August 1830 (Hobsbawm and Rudé 1973, Chap. 5), ignoring the small number of incidents that took place earlier in the summer. We include these in our analysis.

Most of the rioters were landless farm laborers who worked for tenant farmers on daily or weekly wage contracts. These laborers and their families lived in extreme poverty, a situation that had worsened due to a failed harvest in 1829 and the adoption of the threshing machine. The demands of the rioters were therefore largely economic in nature − higher wages, separation of poor law subsidies from wage payments, and more work − and were directed towards local tenant farmers and parish officials. However, a significant minority of the rioters belonged to the class of village craftsmen and traders, many of whom, unlike the farm laborers, were literate.[6]

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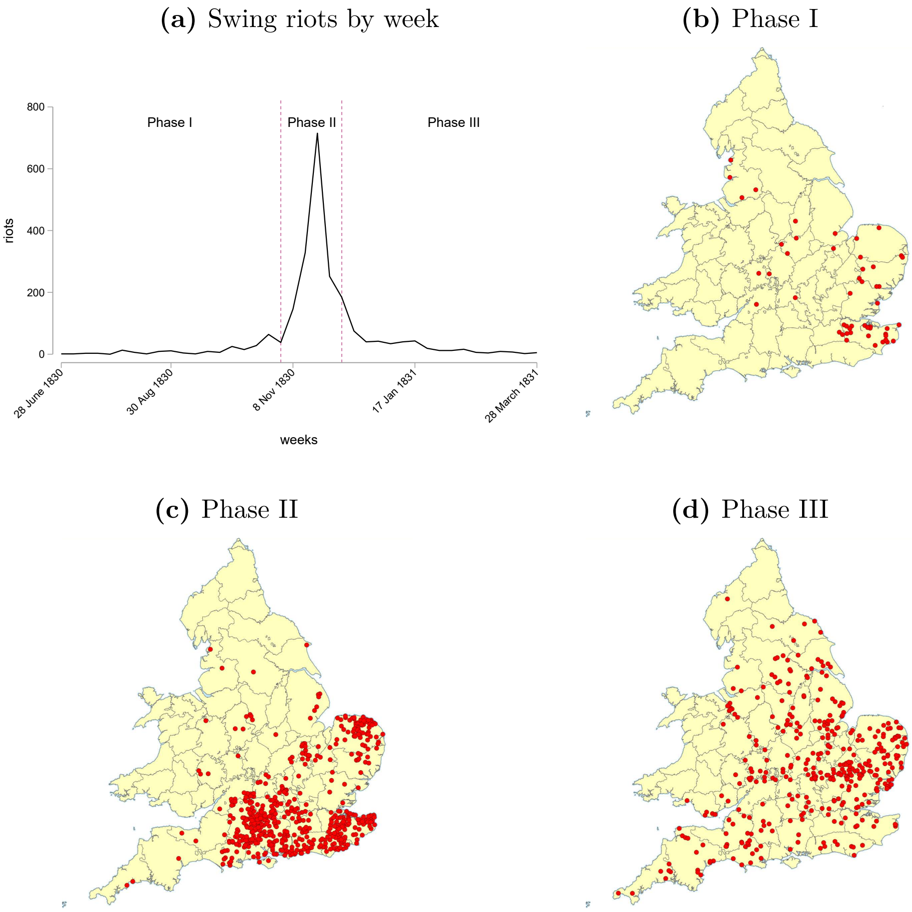
[5] For example, the online appendix presents evidence that strongly suggests that riots near places where newspapers were published were not more likely to be reported.

[6] The limited data on occupation suggests that about 16 percent of arrested rioters were village craftsmen and traders (Holland 2005).

Figure 2: The frequency and spatial distribution of the Swing Riots



Notes: Panel (a) shows the number of Swing riots by week; panel (b) shows the location of the riots during phase I (June to October); panel (c) shows phase II (November); and panel (d) shows phase III (December to March). 28 March 1831 refers to the Monday of the week ending on Sunday, 3 April 1831. Sources: Hobsbawm and Rudé (1973, Appendix III) and Holland (2005).

The riots took a number of different forms: 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] Figure 2(a) plots the total number of

[7] The Swing riots were a national wave of unrest in which participants engaged in a variety of actions, all of which were part of their repertoire of contention (Tarrow 2011). Table A1 in the online appendix reports the number of incidents by type of activity. The historiographical literature refers to all Swing-related incidents as riots, and for consistency we do so too. Riots here should then be understood as incidents of small-scale violence that were part of one single wave of contention. This definition differs from that used in other studies in the literature. For example, Wilkinson (2004) only includes cases in which two or more groups associated with different communities confronted each other.

riots per week between June 28 1830 and April 3 1831: the riots started in Kent, gained momentum in October, peaked in late November, and had largely ended by February 1831.[8] The maps in Figure 2(b,c,d) show the three phases of the unrest as described in Hobsbawm and Rudé (1973). The first was largely contained within Kent. The second saw the riots spread rapidly to the cereal-producing areas of the southeast, the Midlands and East Anglia. In the third phase the riots spread throughout the rest of England. Since the Swing riots spread across a vast area in the space of 40 weeks, it is unlikely that they were the work of a few roaming bands of rioters. Furthermore, data on convicted rioters compiled by Holland (2005, Appendix I) lists over 1,600 different participants, which again suggests that the riots were not the work of a few individuals.[9]

The local authorities were slow to respond. In some cases they made concessions to the rioters, but often they lacked the power to do so. In other instances they tried to repress the riots, but for this they relied on local volunteers who in many cases sympathized with the rioters and refused to help. The rioting eventually came to an end in the early months of 1831 due to three factors: parishes were small and only had a limited number of potential targets, the approaching end of winter meant more employment opportunities in arable farming, and a sudden and unexpected change in government led to an increase in repression.[10]

In addition to the riots data, we digitized and geocoded archival data on the location and timing of local fairs (Owen 1827), the location of stops in the stage-coach network

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[8] There is no consensus among social historians (e.g., Hobsbawm and Rudé 1973, Chap. 4) as to why the riots started in Kent, and it is likely that this was a coincidence. The economic situation in Kent was not worse than it was in any of the other cereal-producing counties of south-eastern England.

[9] Charlesworth (1979, p. 28) studies the speed at which the riots spread along the main stage-coach routes to London and concludes that "such slow speeds mean that we can discount any thought of a conspiracy by agitators traveling by coach." Moreover, there is no convincing historical evidence for any form of national coordination, and the national (radical) leaders do not appear to have been involved (Jones 2009).

[10] The Whigs assumed power in November 1830 and within a month had arrested 2,000 rioters. A special commission sentenced many of them to death or deportation.

(Bates 1969), the location where newspapers were published (House of Commons 1833), and the number of petitions each parish sent to parliament between 1828 and 1831 on the issues of slavery, parliamentary reform and Catholic rights (House of Commons 1831).[11] We lack detailed data on local repression; instead, we use arrests as a proxy, since the number of arrests would have sent a signal to potential rioters about the risks involved.

These variables are likely correlated with a large number of socio-economic factors that could have affected whether a parish was vulnerable to riots. We explore this in table A2 in the online appendix, which shows the correlations between our key variables and ten parish-level socio-economic indicators.[12] As expected, in many cases the correlations are high, an issue that is addressed by the empirical strategy we discuss below.

4 The diffusion of the Swing riots

4.1 Research design

The spatiotemporal variation in our data allows us to address the reverse Galton problem and separate the effect of clustered fundamentals and shocks from that of diffusion. We measure diffusion by looking at the spatial lag of riots; the coefficient on this variable tells us the extent to which riots in a parish result from riots in nearby areas. The Swing riots spread relatively slowly because information at the time traveled at a low speed, generating time variation in exposure to riots nearby that is observable; at the same time, the riots spread fast enough to render all parish-level economic and social fundamentals

[11] Table ?? at the end of the paper reports the descriptive statistics for these variables.

[12] The locations of fairs and arrests do not correlate with any of the indicators. There are more coach stops near London, but otherwise the indicators do not correlate with the presence of a coach stop. The presence of a newspaper is positively correlated with factors related to urbanization, including the number of traders and professionals and the presence of a police station. Finally, the number of petitions sent by a parish is positively correlated with a large number of indicators, including the population of the parish, the number of traders and professionals, and the number of families employed in agriculture. Aidt and Leon (2020) examine the relationship between a number of different structural factors and the incidence of riots.

approximately fixed. Our identification strategy relies on the plausible assumption that these fundamentals either exhibited no time variation in the 40 weeks of unrest, and so can be picked up by parish fixed effects, or that their variation can be captured with week dummies and location-specific time effects. This allows us to remove the effect of clustered fundamentals and shocks, leaving us only with diffusion.[13]

The units of observation are combinations of the 10,335 English parishes and the 40 weeks between Monday, 28th June 1830 and Sunday, 3rd April 1831. Our baseline specification is

$$\mathbf{riots_t} = \pi + \omega_t \iota + \sum_{s=1}^{L} \beta_s \times \mathbf{W} \times \mathbf{riots_{t-s}} + \sum_{r=1}^{L} \lambda_r \mathbf{riots_{t-r}} + \mathbf{u_t}, \tag{1}$$

where $\mathbf{riots_t}$ is an $n \times 1$ vector where element i corresponds to the number of riots in parish i in week t. On the right-hand side, π is an $n \times 1$ vector of parish fixed effects that capture all time-invariant parish-level factors; ω_t is a scalar week effect and ι is an $n \times 1$ vector of ones, and these capture time shocks common to all parishes.[14] The term $\sum_{s=1}^{L} \beta_s \times \mathbf{W} \times \mathbf{riots_{t-s}}$ is the spatial lag, where β_s is a parameter and $\mathbf{W}$ is a $n \times n$ weight matrix where element (i, j) equals 1 if parishes i and j are neighbors (their centroids are within 10km of each other) and 0 otherwise.[15] This term therefore involves time lags of

[13] This is equivalent to the identification assumption described in Plümper and Neumayer (2010): "Identification rests on the assumption that all of the spatial patterning of the dependent variable that has nothing to do with spatial dependence itself is fully explained by the independent variables other than the spatial lag" (p. 427).

[14] In table A3 in the online appendix we show that our results are robust to using parish-days as the unit of observation.

[15] The choice of our weight matrix is motivated by theory, as recommended by Plümper and Neumayer (2010): the total number of riots in the neighborhood (rather than the average across neighboring parishes) is likely to be the measure that matters for diffusion. In the online appendix we replicate some of our estimates using a row-normalized matrix and the results are consistent with what is presented here. The 10km radius used to create the neighborhoods is chosen on the basis of historical evidence that suggests that this is as far as most farm laborers would typically travel (e.g., Hobsbawm and Rudé 1973, p. 212). In table A7 in the online appendix we show that our results are robust to increasing this radius.

the spatial lag, and captures the effect of riots in neighboring parishes at different times in the past.[16] The term $\sum_{r=1}^{L} \lambda_r \mathbf{riots_{t-r}}$ includes time lags of own riots where L is the number of lags and λ_r is a coefficient; this captures the history of riots within a parish and helps account for temporal dynamics. The term $\mathbf{u_t}$ is a $n \times 1$ vector of errors, which includes unobserved factors.

We estimate equation (1) with the least squares dependent variable (LSDV) estimator, adjusting the standard errors to account for heteroskedasticity, serial autocorrelation and spatial correlation between parishes that are within 10km of each other using the method in Conley (1999).[17] We employ this OLS estimator (and so we run S-OLS) because Franzese and Hays (2007) show that when the size of the spatial lag is under 0.3, S-OLS and S-MLE produce similar results.[18] We later show that our results are robust to using a S-MLE specification.

4.2 Personal networks

Information about the Swing riots could have been transmitted locally between friends and family (Hobsbawm and Rudé 1973, p. 189) or between farm laborers who lived near each other (Griffin 2012, p. 133). We can test for the importance of these personal networks by quantifying diffusion at the local level. The specification in equation (1) captures this effect and table 1 reports the estimation results. Column (1) presents a simple regression that shows that diffusion is positive and significant. The coefficient on $\mathbf{W} \times \mathbf{riots_{t-1}}$ isolates diffusion under the assumption that clustered fundamentals and time shocks are picked up by the parish and week fixed effects, and can be interpreted as the direct effect that an

[16] Anselin (1988) shows that the presence of a spatial lag causes OLS estimates to be biased and inconsistent. We address this by time-lagging the spatial lag, as suggested by Ward and Gleditsch (2008).

[17] It is common to assume that the residuals follow a normal distribution, but this assumption is not necessary in samples as large as ours. We discuss this in more detail in the online appendix.

[18] Franzese and Hays (2007) conclude that "modest interdependence strength and imperfect exogeneity of instruments – common conditions, we suspect – favor adequacy of the simpler LS over the IV or ML spatial estimators" (p.157).

Table 1: Diffusion

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$	(4) $\mathbf{riots_t}$	(5) $\mathbf{riotsO_t}$	(6) $\mathbf{riots_t}$	(7) $\mathbf{riots_t}$	(8) $\mathbf{riots_t}$
$\mathbf{W} \times \mathbf{riots_{t-1}}$	0.0029	0.0029	0.0020	0.0039	0.0016	0.0032	0.012	0.0023
	(0.00096)**	(0.00091)**	(0.00088)*	(0.00076)***	(0.00022)***	(0.00092)***	(0.0049)*	(0.00025)***
$\mathbf{W} \times \mathbf{riots_{t-2}}$						-0.00017		
						(0.00050)		
$\mathbf{W} \times \mathbf{riots_{t-3}}$						0.000088		
						(0.00055)		
$\mathbf{riots_{t-1}}$	0.032	-0.055	-0.065	-0.038		-0.076	-0.254	0.033
	(0.016)*	(0.018)**	(0.023)**	(0.015)*		(0.019)***	(0.031)***	(0.0016)***
$\mathbf{riots_{t-2}}$						-0.12		
						(0.014)***		
$\mathbf{riots_{t-3}}$						-0.12		
						(0.015)***		
Observations	403,065	403,065	403,065	403,065	384,142	382,395	403,065	403,065
Fixed effect	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish
Time dummies	Weeks	Weeks	Weeks	Weeks	Weeks	Weeks	Weeks	Weeks
Time trend	None	parish x period	parish x period	parish x period	parish x period	parish x period	None	None
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Bootstrap	spatially-adjusted
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson	MLE
Note			large riots only	small riots only				

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. In columns (1) to (6) the standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). The parish $\times$ period effects are constructed by interacting the parish dummies with four period dummies, each corresponding to a 10-week subset of the 40 weeks of unrest. The vector $\mathbf{riotsO_t}$ in column (5) measures riot onset, with element i being equal to 0 if by time t no riot has taken place in parish i, and equal to 1 if the first riot in parish i occurs at time t. The variable is coded as missing if a riot has taken place in i at any time prior to t, which explains the drop in the number of observations. The coefficients in column (7) are conditional fixed effects ML Poisson regression coefficients. Column (8) estimates the specification in column (1) but uses a maximum likelihood estimator with the errors adjusted for arbitrary spatial correlation across neighboring parishes.

additional riot in the neighborhood of parish i in week $t-1$ has on riots in i in week t. This interpretation as a marginal effect is possible because the spatial lag enters the panel model with a one week lag. The effect is large: one additional riot near i results in an additional 0.0029 riots in i the following week, which is more than half the size of the number of riots experienced in the average parish-week (0.0054, as reported in table **??** in the appendix).

It is also informative to examine the size of the effect that results from a typical within-parish change in the number of riots in the neighborhood.[19] To do this we compute the within variation for each parish, take its average across parishes, and use this value to calculate the size of the effect. The average within-parish variation in the independent variable is 4.677, leading to an effect of $4.677 \times 0.0029 = 0.014$. That is, an increase in nearby riots that is equal to the average within-parish variation results in an additional 0.014 riots; this is 2.5 times the baseline probability of a riot in the sample (0.0054, as reported in table **??** in the appendix.).[20]

These results are about how a parish is affected by one of its neighbors, but we can turn this question around and consider how a parish affects its neighbors. To do this, we calculate the effect that an additional riot in a parish j at time t would have on the total number of riots in its neighborhood at $t+1$. This requires that we add up the effect of that additional riot on each of j's neighbors, which is approximately equal to the spatial lag coefficient times the average number of neighbors (which is 34); that is $0.0029 \times 34 = 0.10$.[21]

[19] When using fixed effects, the size of the effect implied by the coefficient needs to be calculated relative to a plausible within-unit change in the independent variable (Mummolo and Peterson 2018). Otherwise we may end up calculating the effect using a variation that, although present across units, is too large to occur within units.

[20] The maximum variation within a parish was 80.2. To get a sense for the how large the effects could be in some parishes, consider Chilton Foliat in Wiltshire, which had 79 riots in its neighborhood in the third week of November 1830. The same calculation as above leads to $0.0029 \times 79 = 0.23$, which is 42 times the size of the average number of riots across parish-weeks.

[21] We can also compute the cumulative long-term effect of this riot after s periods by adding the effects at $t+1, t+2, ..., t+s$. The cumulative effect will depend on where the initial riot takes place, but the mean long-term effect converges to 0.13. This effect is much greater for parishes with an above-average number of neighbors, including many in Kent

The coefficient 0.0029 is an average across weeks, but we can also estimate a specification where the coefficient on a binary version of the spatial lag is allowed to vary by week.[22] We do this by following the method developed in Hainmueller, Mummolo, and Xu (2019), which relaxes the linearity assumption implicit in standard interaction formulations and checks for common support across the range of the conditioning variable (which in our case is *weeks*). Figure 3 shows the results. In panel (a) we plot the conditional marginal effects from a binning estimator, which shows that in the early weeks the diffusion generated by a nearby riot was increasing with time. This then drops suddenly after December. In the middle weeks, the coefficients are around 0.05; multiplying this by 34 (the average number of neighbors) gives 1.7, meaning that an additional riot in j in these middle weeks would have generated on average more than one riot in j's neighborhood the following week. This is the explosive phase of the process. The fact that these coefficients then fall is consistent with the riots slowing down and eventually ending.[23] Panel (b) repeats the analysis using a kernel smoothing estimator of the marginal effects, and confirms the findings from panel (a).

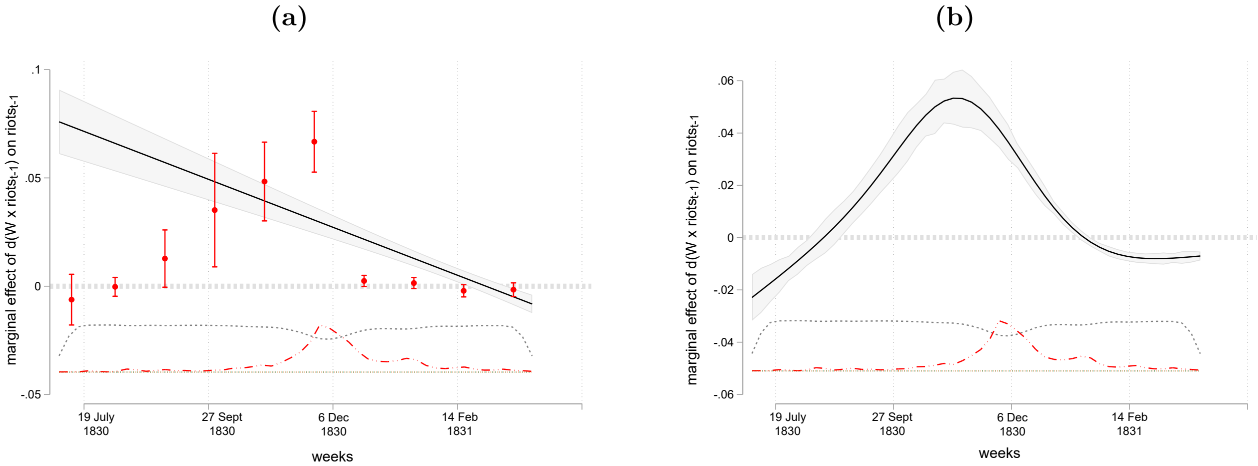
The assumption that clustered fundamentals and time shocks are picked up by the parish and week effects would be violated if some parishes were affected by correlated shocks that varied across time and space. In column (2) of table 1 we add parish $\times$ period effects that we construct by interacting the parish dummies with four period dummies, each corresponding to one of the 10 week sub-periods into which the 40 weeks in our data can be divided. This is a flexible way to control for parish-specific time trends. The results do not change much, suggesting that this is not a major concern.

(where the riots started), which have over 100 neighbors. See the online appendix for the derivation of this result.

[22] The dummy equals 1 if there was at least one riot in the 10km neighborhood of the parish at $t-1$.

[23] The bottom of panel (a) shows treated units (those with at least one riot nearby) in dashes and control units (those with none) in dots, by week. Most of the treatment occurs in the middle range, where the coefficients are positive. This again is consistent with an explosive process that starts suddenly and ends quickly.

Figure 3: Spatial coefficients by week



Notes: This figure shows the coefficients on a binary version of the spatial lag, $\mathbf{d(W \times riots_{t\text{-}1})}$, by week. $\mathbf{d(W \times riots_{t\text{-}1})}$ is a vector of length n where element i equals 1 if there was at least one riot within 10km of parish i at time $t-1$. The coefficients are estimated by interacting the spatial lag with week dummies using the interflex package (Hainmueller, Mummolo, and Xu 2019). In panel (a) we show the conditional marginal effects from a binning estimator (using 10 bins). Panel (b) shows the results for a kernel smoothing estimator of the marginal effects. The dashed line at the bottom shows the frequency distribution of treated parishes across weeks (where a parish is treated if it had at least one riot nearby at $t-1$); the dotted line is the frequency distribution for non-treated parishes. The estimates control for $\mathbf{riots_{t-1}}$ and include both parish and week effects. Standard errors are bootstrapped and we show 95% confidence intervals.

The Swing rioters engaged in a variety of actions, all of which were part of their repertoire of contention (McAdam, Tarrow, and Tilly 2001, p.16). It is possible that different actions spread in different ways. In column (3) we show the results for regressions that only consider types of incidents that were 'large' (those that tended to have 10 or more participants), while in column (4) we show results that only include those types of incidents that were 'small' (those with fewer than 10 participants). Large incidents include machine breaking, robbery, wage and tithe riots, and the rescue of prisoners; while small incidents include arson, attempted arson, damage to crops, fences and other property, animal maiming and Swing letters.[24] We find that the coefficient for small incidents is twice as large as that for large incidents, and an F-test rejects the null of equality at the 5 percent level. It is perhaps not surprising that small incidents diffused more, since they involved activities that could be easily replicated elsewhere. Large actions, on the other hand, required more coordination

[24] There are 1,339 large incidents and 890 small incidents in our dataset. The classification is based on estimates of the approximate number of individuals involved by type of incident, derived using the data in Horn and Tilly (1988). See the online appendix for more details.

and involved activities (e.g. machine breaking) that were only possible in specific locations (i.e. where there was a machine to break).

The time lag of the spatial lag eliminates the problem of simultaneity, but reverse causality is still possible: a riot in parish i at time t can lead to a riot in parish j at time $t+1$, and then this riot might itself lead to a riot in i at $t+2$. We address this by focusing on the onset of riots in a parish, since by definition there can be no reverse causality. We define a new $n \times 1$ vector $\mathbf{riotsO_t}$ that measures riot onset, with element i being equal to 0 if by time t no riot has taken place in parish i, and equal to 1 if the first riot in parish i occurs at time t. The variable is coded as missing if a riot has occurred at any time prior to t, so that the parish exits the sample the week after it experiences its first riot; consequently, it cannot experience the feedback from the effect its riots have on its neighbors. Column (5) presents estimates of the probability of onset as a function of riots in the parish's neighborhood. The point estimate on $\mathbf{W} \times \mathbf{riots_{t-1}}$ is roughly half that in column (2), suggesting that feedback from parish i back to itself through neighboring parishes may be of some importance.

We have implemented a large number of additional robustness checks, three of which are shown in table 1. Column (6) shows the results when we include three temporal lags, and our main findings are unchanged.[25] Column (7) reports the results from using a conditional fixed effects ML Poisson estimator that treats the number of riots in a parish as a count variable.[26] The coefficients are different and have a different interpretation, but the signs and significance levels are consistent with the results reported in the other columns. Column (8) presents the results from using maximum likelihood (instead of OLS) to estimate the coefficients. As discussed earlier, because of our setting and specification, we expect both maximum likelihood and OLS to produce similar results, and that is indeed the case.[27]

[25] Table A5 in the online appendix reports the results for a specification with up to ten temporal lags.

[26] This estimator is robust to the violation of the assumption that the mean and variance of the dependent variable are the same, and so we do not need to use a negative binomial estimator.

[27] Table A6 in the online appendix shows that our results are robust to excluding the county of Kent (where the riots started) and excluding all parishes within 20km of Lon-

In conclusion, our results provide strong support for the hypothesis that local personal networks are key to the spread of riots: individuals participate because their neighbors do. The existing quantitative literature has often examined diffusion by looking at how social unrest spreads across cities – for example, Myers (2010) examined the spread of race riots in the 1960s across cities in the US, while Andrews and Biggs (2006) examined the diffusion of sit-ins in the American south – but the use of cities as the unit of analysis means that these studies cannot estimate the role played by very local networks. We show that these local networks play an important role in the spread of unrest, confirming a number of previous accounts including those of the 1967 riots in Detroit (Singer, Osborne, and Geschwender 1970), the 1871 Paris Commune (Gould 1991), and the Arab Spring protests in Egypt (Hassanpour 2017).

4.3 Trade networks (fairs)

Regional trade in the 1830s was centered around market towns and fairs. People from the surrounding countryside would come to these locations to trade, and in the process exchanged information about local events (Hobsbawm and Rudé 1973, p. 188). News about the Swing riots could have been shared at the fairs, and then spread into the surrounding countryside as people returned home. This information could in turn have spurred new riots. For example, news of concessions by the local authorities appear to have spread during the fair held in Norwich on November 27 1830, and two days later rioting broke out in several parishes around the city (Charlesworth 1979, p. 20-24).

We examine whether diffusion was higher near the site of a fair in the weeks after it was held. The advantage of working with fairs is that they were large regional events that took place once or twice a year, and so exhibit time variation.[28] We use data on the location and dates of all fairs, which were fixed to coincide with important events in the calendar (e.g. Easter). Although the location of a fair could be endogenous, its *timing* is plausibly exogenous as it is unlikely to have been affected by factors related to the riots.[29] For

don. Table A7 in the online appendix shows that the results are robust to increasing the neighborhood radius to 20km.

[28] This is unlike markets, which were regular events that happened at least once a week.

[29] There is no evidence of fairs being canceled as a result of the riots.

example, fairs in the southeast, an area that grew cereals, did not disproportionately happen in winter.[30] Since our estimation strategy exploits variation over time within parishes (in terms of whether a fair is taking place nearby), endogeneity is unlikely to be an issue.

We augment equation (1) by adding a $n \times 1$ vector $\mathbf{d(fairsN_{t\text{-}1})}$ that has element i equal to 1 if a fair took place within a 10km radius of parish i at $t-1$, and equal to 0 otherwise. Column 1 in figure 4 shows that the coefficient on this vector is positive and significant: parishes near the location of a fair experienced more riots the week after the fair had taken place. To get a better sense for whether the fairs helped spread information about the riots, we split the effect of fairs into two depending on whether there were riots near the fair in the week it happened.[31] We do this by interacting $\mathbf{D(fairsN_{t\text{-}1})}$, a $n \times n$ matrix where element (i, i) is 1 if there was a fair near parish i at $t-1$ and all other elements are 0, with $\mathbf{d(riots\ near\ fair_{t\text{-}1})}$, which is a $n \times 1$ vector where element i equals 1 if at $t-1$ there was at least one riot within 10km of a fair that is near parish i, and 0 otherwise.[32] Column 2 in figure 4 shows that the explanatory power of fairs is largely taken up by this interaction, suggesting that fairs fueled diffusion only when there had been riots in their vicinity. The effect is large: it is ten times bigger than the coefficient on $\mathbf{d(fairsN_{t\text{-}1})}$. This is consistent with the hypothesis that fairs served as local information hubs where individuals exchanged news about what was happening in the surrounding countryside.[33]

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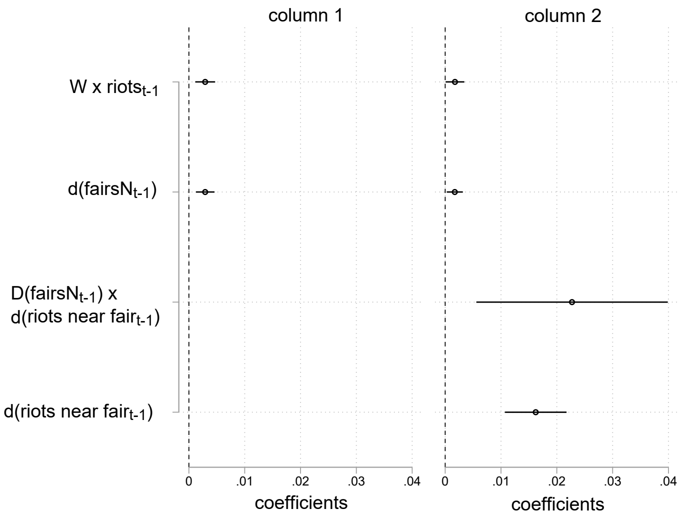
[30] There is no discernible pattern to when or where fairs were held, and the presence of a fair in a parish does not correlate with any of our observable, parish-level socio-economic indicators (see table A2 in the online appendix). Over 97% of parishes were within 10km of a location that held a fair during the period of unrest. Figure A3 in the online appendix shows the location of fairs.

[31] The reasoning is that information about riots near the fair would have spread between individuals attending that fair, who then would have brought this information back home with them.

[32] We use a binary version of this variable in order to reduce the potential effect of outliers.

[33] Table A12 in the online appendix shows that the results are robust to restricting our analysis to large incidents only.

Figure 4: Fairs



Notes: This figure shows coefficients and their 95% confidence intervals. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). In column 1 we include $\mathbf{W} \times \mathbf{riots_{t\text{-}1}}$ and $\mathbf{d(fairsN_{t\text{-}1})}$, where $\mathbf{d}(\mathbf{fairsN_{t-1}})$ is a $n \times 1$ vector where element i equals 1 if at least one fair occurred within 10km of parish i's centroid in week $t-1$, and 0 otherwise. In column 2 we add $\mathbf{d(riots\ near\ fair_{t\text{-}1})}$ which is a $n \times 1$ vector where element i equals 1 if in week $t-1$ there was at least one riot within 10km of a fair that is near i, and 0 otherwise. We also include the interaction $\mathbf{D}(\mathbf{fairsN_{t-1}}) \times \mathbf{d}(\mathbf{riots\ near\ fair_{t-1}})$, where $\mathbf{D(fairsN_{t\text{-}1})}$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if at least one fair occurred within 10km of parish i's centroid in week $t-1$; and all other elements are 0. A sample size of 403,065 was used in these estimations. Table A8 in the online appendix reports the complete regression results from which these coefficients are taken.

We find support for our hypothesis that locations near trade hubs experience more diffusion; at these locations, market traders and laborers appear to have exchanged information about the local riots, possibly as gossip and without the intention of causing the riots to spread (Allport and Postman 1947; Bhavnani, Findley, and Kuklinski 2009). This shows that unrest can spread along trade networks, a hypothesis that is difficult to test in other contexts because changes in trade are typically endogenous. In doing so we provide quantitative evidence for the claim that dense information networks formed through market transactions can facilitate the spread of riots (Bohstedt and Williams 1988; Rudé 1964). However, our conclusions differ from those of a recent empirical literature that views trade as a factor that facilitates peace. For example, Jha (2013) finds that trading ports in South Asia were less prone to the onset of inter-ethnic violence than inland cities, because complementarities in trade led to the emergence of institutions that fostered cooperation between ethnic groups. We focus on diffusion and on a different type of violence, and find that trade brought together individuals that otherwise would not have mixed, allowing them to exchange information that facilitated the spread of the riots.

4.4 Transport networks (coach stops)

The Swing riots predate the construction of the railroads, and so the stagecoach was the main form of public transport, with coaches traveling along the existing turnpike roads and making stops at pre-established locations (Albert 1972). Travelers along these roads could have met local laborers and activists near the coach stops and told them about the riots in other parts of the country. Consequently, proximity to a coach stop could have improved a parish's access to information about the riots.

We test for the effect of transport networks on diffusion by examining whether diffusion was greater in parishes near coach stops.[34] To do the estimation we introduce the $n \times n$ matrix $\mathbf{D(coachstopN)}$ where element (i, i) equals 1 if parish i was within 10km of a coach stop and all other elements are 0. We interact this with $\mathbf{d(W \times riots_{t-1})}$, which is a binary version of the spatial lag where element i equals 1 if there was at least one riot in the neighborhood of i at time $t-1$ (and all other elements are 0). Figure 5 shows that this interaction is statistically insignificant.[35]

There is a growing quantitative literature that studies the importance of transport networks in facilitating the diffusion of social unrest: Brooke and Ketchley (2018) show that the spread of the Muslim Brotherhood in Egypt was facilitated by the railways, Ketchley and Brooke (2018) show that the Brotherhood was more likely to mobilize near mosques that were accessible by tram, and Cunningham and Phillips (2007) show that state routes and highways aided in the expansion of the Ku Klux Klan in North Carolina. These studies build on an older qualitative literature; for example, Skocpol (1997) argues that the stagecoach was an important factor in the development of civil associations in the United States, while Pethybridge (1972) suggests that the success of the Bolsheviks was in part due to their use

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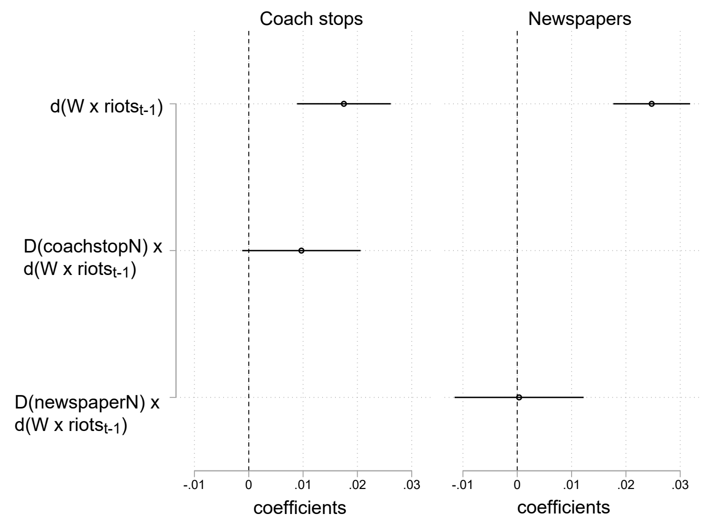
[34] The location of coach stops is endogenous; in particular, the density of coach stops was much higher in parishes near London (see table A2 in the online appendix). This means that the estimation coefficients partly reflect a "proximity to London" effect, which could have affected rioting directly. Figure A4 in the online appendix shows the location of the coach stops.

[35] The dummy variable that captures proximity to a coach stop drops out of the estimation because it exhibits no time variation. Table A13 in the online appendix shows that the results are robust to restricting our analysis to large incidents only.

Figure 5: Coach stops and newspapers



Notes: These figures show the coefficients of interest with their 95% confidence interval. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). $\mathbf{d(W \times riots_{t-1})}$ is a vector of length n where element i equals 1 if there was at least one riot within 10km of i at time $t-1$ and 0 otherwise, $\mathbf{D(coachstopN)}$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if parish i is within 10km of a coach stop and 0 otherwise, and $\mathbf{D(newspapersN)}$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if parish i is within 10km of where a newspaper was published and 0 otherwise. A sample size of 403,065 was used in these estimations. The complete regression results can be found in table A9 in the online appendix.

of the railway system. Most of these studies look at diffusion over a relatively long period of time; we show that in situations where diffusion happens very quickly, as is often the case with social unrest, the transport network appears to play no role. Moreover, in most of the cases considered by these studies there was a considerable amount of centralized organization; we show that social unrest that is not centrally organized does not appear to spread through the transport network.

4.5 Media networks (newspapers)

Newspapers were the only form of mass media at the time of the Swing riots. Local and national newspapers reported extensively on the riots and on the authorities' response to them, with the first reports appearing in the *Standard* and *The Times* on September 27 1830. Farm laborers were mostly illiterate, and so if information from the newspapers reached them, it is likely to have been through local activists who either organized the riots or used the information to inspire farm laborers to mobilize (Charlesworth 1979). Our hypothesis is that these effects were stronger in areas where local newspapers were published, which we test by estimating whether there was more diffusion in parishes near towns with a local newspaper. To do the estimation we introduce the $n \times n$ matrix $\mathbf{D(newspaperN)}$ where element (i, i) equals 1 if parish i was within 10km of where a newspaper was published, and all other elements are 0. We interact this with the $n \times 1$ vector $\mathbf{d(W \times riots_{t\text{-}1})}$.[36] Figure 5 shows that the estimated coefficient on the interaction term is zero; we find no evidence to support the hypothesis that the mass media affected diffusion during the Swing riots.[37]

Our findings stand in contrast to a large literature that emphasizes the role of the media in facilitating the spread of unrest. For example, Myers (2000b) finds that media networks were important in driving the spread of race riots across cities in the US, while Andrews and Biggs (2006) show that it facilitated the diffusion of sit-ins in the American South. Traditional forms of media continue to be important: interviews with participants in the 2011 London riots suggest that many of them learned about the riots from television news reports (Morrell et al. 2011). Recently this literature has shifted its attention to social media; for example, Vasi and Suh (2016) show that the Occupy movement used Facebook to grow and spread, Enikolopov, Makarin, and Petrova (2020) show that the penetration of VKontakte (the Russian equivalent to Facebook) facilitated the spread of the post-election protests in 2011, and Hassanpour (2014) finds that activity on social media helped mobilize protesters in Egypt's Arab Spring. On the other hand, some studies have shown that the mass media can help deter unrest, for example if it is used by the government to transmit threats to potential participants (e.g. Hassanpour 2017).

5 The information transmitted

What did the farm laborers and local activists learn from the riots in other parishes? Our framework distinguishes between information about the riots themselves, which could

[36] The location of newspapers was not random, and table A2 in the online appendix shows that the presence of a newspaper was correlated with measures of urbanization. Figure A4 in the online appendix shows the locations where newspapers were published.

[37] The dummy variable that captures proximity to a newspaper drops out of the estimation because it exhibits no time variation. Table A13 in the online appendix shows that the results are robust to restricting our analysis to large incidents only.

have provided inspiration and ideas about new actions in the repertoire, and information about the local authorities' response, which would have affected individuals' cost-benefit calculations. A key element in this cost-benefit calculation is the likelihood of punishment.[38] Historical accounts suggest that the lack of an effective response in the early weeks of the riots allowed them to spread. For example, following the arrest of some of the first machine-breakers, "the intensity of protests declined immediately thereafter .... [but] the trial of these first machine-breakers and their subsequent sentence of only four days' imprisonment – against the maximum sentence of seven years' transportation – acted to encourage others to 'rise'. Literally overnight, protests spread rapidly" (Griffin 2012, p. 2).

To understand if the information about the local authorities' response to the riots fueled diffusion, we draw a distinction between riots that led to arrests and those that did not, where arrests serve as a signal to potential rioters about the risks of participation. To capture this effect we include $\mathbf{d(riots_{t\text{-}1})}$ which is a $n \times 1$ vector where element i equals 1 if there were riots in parish i at times $t-1$ and 0 otherwise, $\mathbf{D(repression_{t\text{-}1})}$ which is an $n \times n$ matrix where element (i,i) equals 1 if there were arrests in i at $t-1$ and all other elements are 0, an interaction between these two, the spatial lag $\mathbf{d(W \times riots_{t\text{-}1})}$, $\mathbf{D(repression\ nearby_{t\text{-}1})}$ which is an $n \times n$ matrix where element (i,i) equals 1 if there were arrests within 10km of parish i at $t-1$ and all other elements are 0, and an interaction between these two.[39] Panel (a) in figure 6 reports the results. We find that arrests in i had a negative and significant effect on future riots in i: if the riots in a parish led to arrests, its expected number of riots the following week was significantly lower than it would have been otherwise. This is consistent with the hypothesis that repression discourages future participation. Turning to the spatial lag, we find that the coefficient on the interaction is not significant, so that arrests in nearby areas did not affect the diffusion of those riots.

[38] Another important element is the likelihood of concessions, but we were unable to find systematic data to measure them.

[39] The variable $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ can only be 1 if $\mathbf{d(riots_{t\text{-}1})}_i$ is 1, and so it has the same value as the interaction $\mathbf{D(repression_{t\text{-}1})}_{(i,i)} \times \mathbf{d(riots_{t\text{-}1})}_i$. Consequently, we can only estimate the coefficient on either $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ or the interaction, but not both; in practice the variable $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ is dropped by the estimation. Similar reasoning explains why the variable $\mathbf{D(repression\ nearby_{t\text{-}1})}_{(i,i)}$ is dropped by the estimation.

This suggests that repression in parishes near i had no effect on rioting in i: diffusion was not affected by information about repression.

To summarize, we find that cost-benefit calculations appear to have been relevant to the decision to participate, so that the direct threat of repression affected participation. This supports the view in the rational choice literature that repression reduces an individual's willingness to participate in a riot (e.g., DiPasquale and Glaeser 1998). However, diffusion was not driven by information about the law enforcement response in neighboring parishes, and so the evidence does not support the hypothesis that repression affects diffusion. This suggests that behavioral factors (e.g. imitation) are likely to play an important role in the spread of unrest.

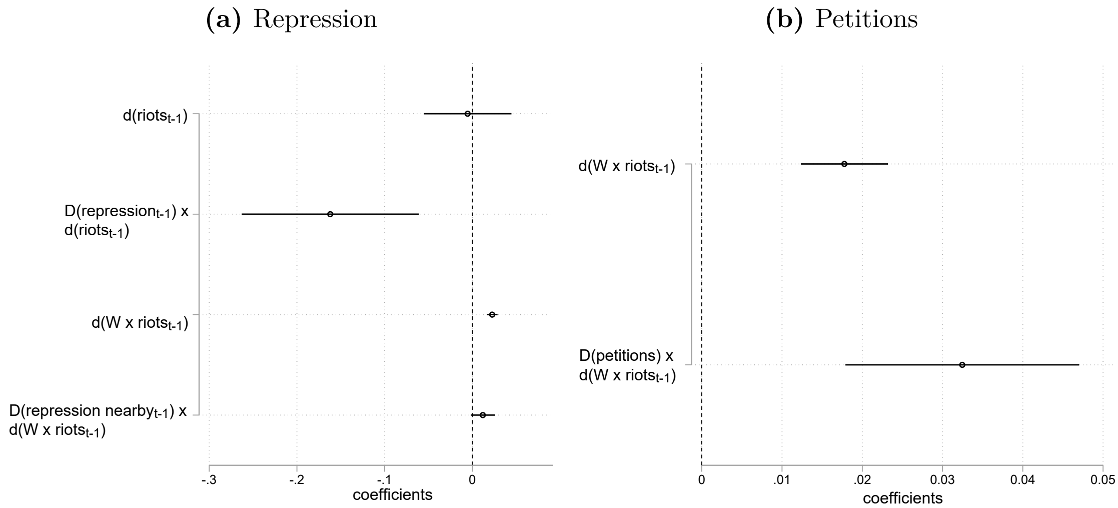
6 The organizers of collective action

The response to the information about nearby riots could have been either spontaneous or organized. If it was organized, we would expect to see the presence of organizers, in this case the local activists who could have spread information about the riots and provided organizational support. In the data we cannot directly observe these local activists, but we can proxy for their presence by looking at other activities in which they would have been involved. One such activity is the writing of petitions to parliament, particularly those concerning the key social issues of the day: parliamentary reform, slavery and the rights of Catholics (Leys 1955). It is likely that more petitions were written in areas with more local activists, and so we can test the hypothesis that riots require the input of organizers by examining whether parishes that sent more petitions also experienced more diffusion. We estimate a specification that includes an interaction between **D(petitions)**, which is a $n \times n$ matrix where element (i, i) equals 1 if parish i sent any petitions between 1828 and 1831 and all other elements are zero, and the spatial lag $\mathbf{d(W \times riots_{t\text{-}1})}$. The results are shown in panel (b) of figure 6.[40] We observe that the estimated coefficient on the interaction is positive and statistically significant, suggesting that parishes that sent petitions experienced more diffusion from nearby parishes.

The spread of the riots appears to have been aided by the presence of local activists. This finding contributes to the debate about whether riots and unrest more generally must

[40] The dummy for petitions is dropped because it has no time variation.

Figure 6: The information transmitted, the organizers



Notes: These figures show the coefficients of interest with their 95% confidence interval. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). $\mathbf{d(riots_{t\text{-}1})}$ is a $n \times 1$ vector where element i equals 1 if there were riots in i at $t-1$ and 0 otherwise, $\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t-1}})$ is a vector of length n where element i equals 1 if there was at least one riot within 10km of i at time $t-1$ and 0 otherwise, $\mathbf{D(repression_{t\text{-}1})}$ is a $n \times n$ matrix where element (i,i) equals 1 if there was repression in parish i at $t-1$ and 0 otherwise, $\mathbf{D(repression\ nearby_{t\text{-}1})}$ is a $n \times n$ matrix where element (i,i) equals 1 if there was repression in parishes within 10km of i at $t-1$ and 0 otherwise, and $\mathbf{D}(\mathbf{petitions})$ is a $n \times n$ diagonal matrix where element (i,i) equals 1 if parish i is sent at least one petition to parliament in 1828-1831 and 0 otherwise. A sample size of 403,065 was used in these estimations. The complete regression results can be found in tables A10 and A11 in the online appendix.

be organized and require leadership. Although much of the literature has focused on non-rational explanations for the spread of riots (e.g. Epstein 2002), a different view is that riots are to some extent organized or facilitated by politicians who control the security forces. For example, Wilkinson (2004) shows that local politicians in India use their power and control over law enforcement to trigger ethnic confrontations as part of their electoral strategy. In other instances the unrest is organized by the groups themselves; for example, Andrews and Biggs (2006) show that movement organizations were important in driving the spread of sit-ins in the 1960s. Our findings show that local organization can play an important role in the diffusion of social unrest.

7 Conclusions

In this article we present a theoretical framework and an empirical strategy for estimating the diffusion of social unrest. We apply the strategy to the case of the Swing riots and show that diffusion was an important factor in driving the unrest. We also examine how the information about the riots was transmitted, what the information was about, and who acted on it. This helps explain why and how diffusion happens, and provides a comprehensive analysis of a process that most of the literature treats as a black box.

The Swing riots are an ideal setting in which to estimate diffusion, as our identification strategy relies on the relatively slow speed at which they spread; this allows us to use time variation to distinguish empirically between diffusion and spatially-clustered fundamentals. But there are other good reasons why the Swing riots are an important case to consider. Hobsbawm and Rudé (1973)'s book on the Swing riots is the foundational text in the study of "popular protest and history from below" (Griffin 2012, p.16), and so this is a natural case in which to test our hypotheses. And the Swing riots are of substantive historical interest too: at the time they made people believe that England was on the brink of revolution, and they played a crucial role in the success of the Great Reform Act of 1832 (Aidt and Franck 2015).

In order to establish the extent to which the mechanisms we have studied generalize to other contexts, our results need to be replicated in other settings. There are a number of important parallels between the Swing riots and more recent episodes of social unrest. For example, social unrest in less developed countries, where individuals have limited access to modern communication technology, must spread in ways similar to the Swing riots. This is also true of unrest in cases where the authorities limit or shut down the phone and internet networks. But the specific ways in which our insights generalize is a question left for future work.

An important issue missing from our analysis is the role that structural factors play in driving social unrest. In the context of the Swing riots, some of these factors have been considered in isolation; for example, Caprettini and Voth (n.d.) show that technological progress can help explain why some parishes experienced riots during this period. But this was a time of rapid social, economic and political change, and so it is possible that other factors played a central role too. This is an important question that requires further examination.

8 Acknowledgements

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10 Appendix

Table 2: Summary statistics

	N	mean	sd	min	max
$\text{riots}_{i,t}$	413,400	0.0054	0.12	0	15
riots $\text{nearby}_{i,t}$	413,400	0.16	1.25	0	88
d($\text{riots}_{i,t}$)	413,440	0.003	0.06	0	1
d(riots $\text{nearby}_{i,t}$)	413,440	0.060	0.24	0	1
d($\text{fairsN}_{i,t}$)	413,400	0.16	0.37	0	1
d(riots near $\text{fair}_{i,t}$)	413,440	0.099	0.30	0	1
d(newspaperN_{i})	413,400	0.22	0.41	0	1
d(coachstopN_{i})	413,400	0.63	0.48	0	1
d($\text{repression}_{i,t}$)	413,440	.0007	0.026	0	1
d(repression $\text{nearby}_{i,t}$)	413,440	0.0135	0.115	0	1
d(petitions_{i})	413,440	0.25	0.43	0	1

Notes: riots $\text{nearby}_{i,t}$ is element i in $\mathbf{W} \times \mathbf{riots_t}$. d($x_{i,t}$) refers to a dummy variable that equals 1 when expression x is true for parish i in week t. d($\text{riots}_{i,t}$) equals 1 if there was at least one riot in i at t, d(riots $\text{nearby}_{i,t}$) equals 1 if there was at least one riot in the 10km neighborhood of i at t, d($\text{fairsN}_{i,t}$) equals 1 if there was a fair within 10km of parish i in week t, d(riots near $\text{fair}_{i,t}$) equals 1 if there was at least one riot at t near a fair that was on at t and was within 10km of i, d(newspaperN_{i}) equals 1 if parish i is within 10km of where a newspaper was published, d(coachstopN_{i}) equals 1 if parish i is within 10km of a coach stop, d($\text{repression}_{i,t}$) equals 1 if there were any Swing-related arrests in i at t, d(repression $\text{nearby}_{i,t}$) equals 1 if there were any Swing-related arrests in the 10km neighborhood of i at t, d(petitions_{i}) equals 1 if parish i sent at least one petition to parliament (on parliamentary reform, slavery or Catholic rights) in 1828-1831.

The Social Dynamics of Collective Action: Evidence from the Diffusion of the Swing Riots, 1830-31*

Online Appendix

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July 23, 2020

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.

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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

2 Variables: definitions and sources

The following variables have both cross-sectional and time variation during the 40 weeks of the riots (between June 28 1830 and April 3 1831):

- $\mathbf{riots_t}$ is an $n \times 1$ vector where element i corresponds to the number of riots recorded in parish i in week t. Source: Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{W} \times \mathbf{riots_{t-1}}$ is an an $n \times 1$ vector where element i corresponds to the total number of riots that took place in week $t-1$ in parishes with centroids within a 10km radius of parish i's centroid. Source: constructed from Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{d(repression_{t-1}})$ is an $n \times 1$ vector of dummy variables where element i equals 1 if there was at least one arrest in i in week $t-1$. Source: Holland (2005, Appendix I). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{d(repression\ nearby_{t-1}})$ is an $n \times 1$ vector of dummy variables where element i equals 1 if there was at least one arrest in a 10km neighborhood of i in week $t-1$. Source: Holland (2005, Appendix I). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{d(fairsN_t})$ is an $n \times 1$ vector where element i is equal to 1 if a parish is 'exposed' to a fair in week t; a parish is exposed to a fair if there is one in a parish with a centroid that is within 10km of its own centroid. The information on fairs comes from Owen (1827), which contains a directory of fairs in England and Wales in 1827.

Geo-referenced using Shaw-Taylor, Satchell, and Newton (2016) and Satchel, Shaw-Taylor, and Potter (2016).

- $\mathbf{d(riotsnearfair_{t-1})}$ is an $n \times 1$ vector where element i is equal to 1 if there was at least one riot at $t-1$ near a fair that was on at $t-1$ and that was within 10km of i.

The following variables only have cross-sectional variation during the 40 weeks of the riots.

- **d(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.

- **d(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).

- **d(petitions)** is an $n \times 1$ vector where element i is equal to 1 if parish i submitted a petition to parliament in the period 1828-1831 and 0 if it did not. We only consider petitions related to the abolition of slavery, parliamentary reform, and rights of Catholics, since these were the three most salient social issues of the time. 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).

3 Descriptive statistics

Incident types: Table A1 shows the different types of Swing riot incidents in our dataset.

Table A1: The 12 most common types of Swing riots incidents

Riot type	**Number of incidents**	**Participants**
Arson	1306	< 10
Attempted arson	54	< 10
Machine breaking (Threshing machines)	538	202
Machine breaking (other agricultural machinery)	47	n.a.
Machine breaking (Industrial machines)	35	n.a.
Sending anonymous threatening letters	270	< 10
Robbery	254	122
Wage riot	289	292
Tithe riot	67	496
Rescue of prisoners and police attacks	102	655
Damage to crops, fences, etc.	32	< 10
Animal maiming	74	< 10

Note: "Number of incidents" refers to the total number of Swing Riot incidents recorded by Holland (2005) for each type. "Participants" is an estimate of the average number of individuals involved in each type of incident, based on the 120 riots recorded by Horn and Tilly (1988) for which this information is available. Sources: Holland (2005), Horn and Tilly (1988).

Holland (2005) does not record estimates of the number of individuals involved in each riot incident. Horn and Tilly (1988), as part of a larger dataset on "Contentious Gatherings in Britain, 1758-1834", record 285 Swing Riot-related incidents (all of which are included in our dataset). These are coded from seven London-based newspapers, with a contentious gathering defined as "an occasion on which a number of people (a minimum of 10) outside of government gathered in a publicly accessible place and made claims on at least one person outside their own number, claims which if realized would affect the interests of their object" (Tilly 1995, p.393). For 120 of these incidents, the underlying sources allowed Horn and Tilly (1988) to estimate the approximate number of individuals involved. Therefore, this information is missing for most incidents, but we are still able to calculate the average number of individuals involved in the different types of incidents, which we record in table

A1. Horn and Tilly (1988) do not record any arson or attempted arson, Swing letters or damage to crops and animal maiming in their catalog of contentious gatherings. It is likely that this is because these events typically did not involve the 10 participants required to qualify as a contentious gathering. Based on this information, we can divide incidents into two groups:

- **Small incidents**: arson, attempted arson, damage to crops, fences and other property, animal maiming, Swing letters.
- **Large incidents**: machine breaking, robbery, wage and tithe riots, rescue of prisoners.

Measurement error: In order to assess whether the newspapers systematically under-reported riots in distant rural areas, in figure A1 we plot two distributions: 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 the riots are indeed 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.[1]

The normality assumption: It is common to assume that the residuals follow a normal distribution. The failure of this assumption does not impact on the bias or consistency of the estimator, but in small samples it affects the p-values used for hypothesis testing (Wooldridge 2003, p.166, p.171). This is because in small samples the normality assumption is required for the t-statistic to follow a t distribution and for the F-statistic to follow an F distribution (p.166, p.171). When normality of the residuals is violated and

[1] 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 brings them closer together than they would have been otherwise. This seems unlikely, especially given that the distributions end up being very similar.

the sample size is small, the test statistics do not follow these distributions. However, this is not an issue when the number of observations is large, since in that case the Central Limit Theorem ensures that the distribution of the t-statistic is approximately t and the distribution of the F-statistic is approximately F (Wooldridge 2003, p.118, p.166, p.171). Whether the sample is large is a relative matter, but the literature refers to numbers like 30 and 200. Our sample size is several orders of magnitude larger, and so the violation of the normality assumption should not affect our hypothesis tests.

Correlation table: table A2 shows the correlations between our key variables and a number of socio-economic fundamentals.

Figure A1: Distribution of distances to newspapers

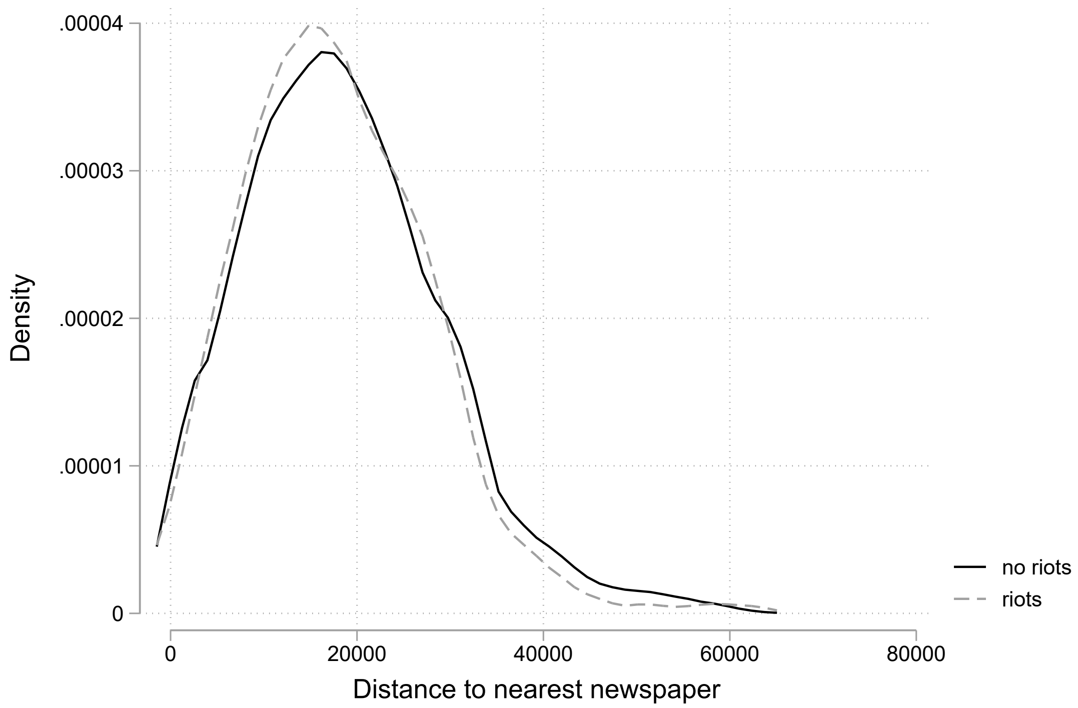


Table A2: Correlations between socio-economic conditions and our key variables

Variables	near fair (10 km)	near newspaper (10 km)	near coach stop (10 km)	log of petitions	repression
cereal	-0.046	-0.080	0.098	-0.037	0.016
log families in agriculture	-0.027	**-0.122**	-0.066	**0.206**	0.016
log population	0.020	0.079	0.047	**0.477**	0.013
log males	0.018	0.074	0.045	**0.478**	0.013
enclosed before 1830	-0.008	-0.051	0.009	**0.137**	0.003
log traders and craftsmen	0.025	**0.105**	0.057	**0.464**	0.011
log professionals	0.046	**0.137**	0.091	**0.442**	0.007
log distance to garrison	0.011	-0.018	-0.012	-0.068	-0.005
near police force (1km)	0.048	**0.192**	0.096	0.044	-0.001
distance to London $<$ 20km	0.048	-0.086	**0.126**	0.058	-0.004

Notes: All correlations greater than 0.1 (in absolute value) are in bold. *near fair (10km)* is a dummy that equals 1 if the parish's centroid is within 10km of the location of a fair, *near newspaper (10km)* is a dummy that equals 1 if the parish's centroid is within 10km of where a newspaper was published, *near coach stops (10km)* is a dummy that equals 1 if the parish's centroid is within 10km of a coach stop, *log of petitions* is the log of the number of petitions sent from parish i, *repression* is a dummy that equals 1 if there were riots in i that were repressed. *cereal* is a dummy that equals 1 if the parish is in a cereal-growing region as shown in Caird (1852). *log families in agriculture*, *log population* and *log males* are all from the 1831 census. *enclosed before 1830* is a dummy that equals 1 if the parish had enclosed prior to 1830 (Tate 1978). *log traders and craftsmen* and *log professionals* measure the number of traders, workers in manufacturing and professionals in the parish, and are all from the 1831 census. *log distance to garrison* calculates the distance to the nearest garrison (War Office, 1830), *near police force (1km)* is a dummy variable that equals 1 if the parish is within 1km of a location with a police force (Clark, 2014), and *distance to London $<$ 20km* is a dummy that equals 1 if the parish's centroid is within 20km of Charing Cross in central London.

3.1 Short- and long-term impact

The fact that we introduce the spatial lag with a one week time lag ensures that we can interpret its coefficient as a marginal effect: it tells us how an increase of one riot in i's neighborhood at time t impacts on the number of riots in i at $t+1$. It is also possible to think about the total impact that an additional riot in a parish j at time t would have: the impact at time $t+1$ would be equal to the sum of the impact on each of j's neighbors (where the average number of neighbors for a parish is 34.26). But the impact will continue over time as neighbors of j impact on their own neighbors at time $t+2$. This means that we can compute a total (cumulative) impact for any time $t+s$ after a one riot increase in a given parish.

To do this we note that recursive substitutions using equation (1) in the main text allow us to write the number of riots at time $t+s$ as a function of the number of riots at time t:

$$\mathbf{riots_{t+s}} = \sum_{r=1}^{s} \mathbf{\Delta}^{r-1}\Big(\pi + \omega_{t+s-(r-1)}\iota + u_{t+s-(r-1)}\Big) + \mathbf{\Delta}^{s}\mathbf{riots}_t,$$

where

$$\mathbf{\Delta} \equiv \beta_1 \times \mathbf{W} + \lambda_1 \times \mathbf{I},$$

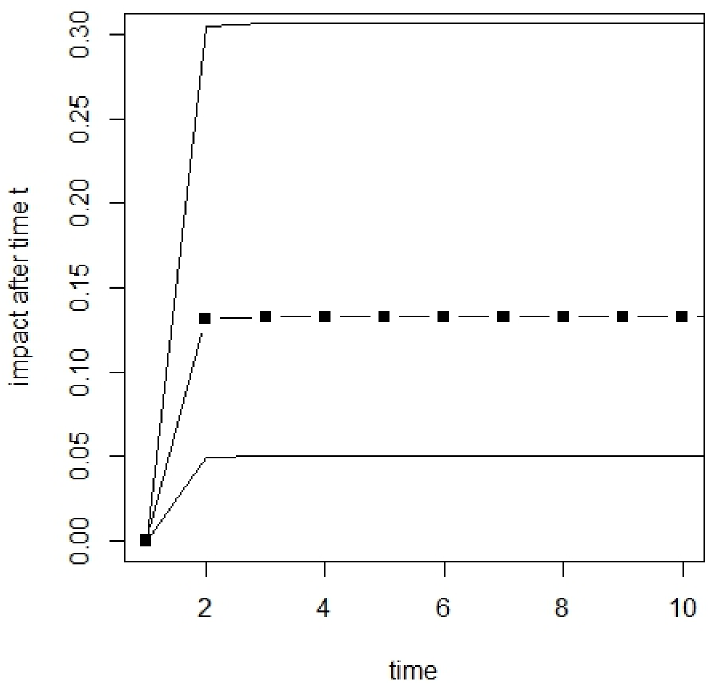
where $\mathbf{W}$ is the weight matrix and $\mathbf{I}$ is an $n \times n$ identity matrix. An increase of one riot in parish j will impact riots at time $t+s$ only through the term $\mathbf{\Delta}^{s}\mathbf{riots}_t$. In particular, the total impact will be equal to the sum of all elements in column j of the matrix $\mathbf{\Delta^s}$, since element (i,j) is equal to the impact that an increase of 1 riot in parish j at time t has on the total number of riots experienced by parish i at $t+s$.

In order to compute to total (cumulative) impact after s periods we need to consider the sum

$$\mathbf{T_{t+s}} \equiv \sum_{r=1}^{s} \mathbf{\Delta}^{r}$$

where $\mathbf{T_{t+s}}$ is an $n \times n$ matrix and the sum of all elements in column j is the total (cumulative) impact of an additional riot in parish j after s periods. Naturally this total will depend on which parish experiences the additional riot, since some parishes are better connected than others in the sense that they have more neighbors (Lower Hardres, where the riots started, has 59 neighbors, and many of its neighbors in Kent have over 100 neighbors). We use the coefficients in column 1 of table 2 ($\beta_1 = 0.0029, \lambda_1 = 0.032$) and plot the average impact for s=1,...,10, together with the 2.5th and 97.5th percentile of the distribution (which then provide us with a 95% confidence interval). The mean impact quickly converges to 0.13, as shown in figure A2.

Figure A2: Total cumulative impact of an additional riot



4 Additional results

Here we show the additional robustness tests referred to in the main text. Table A3 replicates columns 1,2 and 6 of table 1 using daily data. Table A4 replicates the results in columns 1, 2 and 6 of table 1 using a row-normalized matrix. Table A5 returns to using a non-normalized matrix to consider the impact of different lags. Table A6 shows the results are robust to dropping Kent (where the riots started) and London. Table A7 looks at how the results in columns 1,2 and 6 of table 1 change when we increase the neighborhood radius from 10 to 20kms. Tables A8 - A11 show the regression results used to produce the coefficient plots in the text. Tables A12 and A13 replicate the results for fairs, newspapers and coach stops using large riots only.

Table A3: Estimates using daily data

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$
$\mathbf{W \times riots_{t-1}}$	0.011	0.011	0.011
	(0.0022)***	(0.0022)***	(0.0023)***
$\mathbf{W \times riots_{t-2}}$			-0.00031
			(0.00069)
$\mathbf{W \times riots_{t-3}}$			-0.00029
			(0.00040)
$\mathbf{riots_{t-1}}$	0.049	0.037	0.036
	(0.015)***	(0.015)*	(0.015)*
$\mathbf{riots_{t-2}}$			-0.012
			(0.0062)$^{+}$
$\mathbf{riots_{t-3}}$			-0.012
			(0.0049)*
Observations	1,002,495	1,002,495	981,825
Fixed effect	Parish	Parish	Parish
Time dummies	Days	Days	Days
Time trend	No	parish x period	parish x period
Standard errors	Conley	Conley	Conley
Estimation	OLS	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The unit of observation is the parish day, and we examine the riots that took place between Monday 11th October 1830 and Sunday 16th January 1831, which corresponds to the period during which the riots spread and were most intense. The time trends are constructed by interacting parishes with two dummies, one for the period between 11th October 1830 and 28th November 1830 (covering 7 weeks), and another for the period between 29th November 1830 and 16th January 1831 (covering 7 weeks).

Table A4: Estimates with a row-normalized weight matrix

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$
$\mathbf{W^{RN}} \times \mathbf{riots_{t-1}}$	0.085	0.090	0.098
	(0.028)**	(0.027)***	(0.028)***
$\mathbf{W^{RN}} \times \mathbf{riots_{t-2}}$			0.00061
			(0.013)
$\mathbf{W^{RN}} \times \mathbf{riots_{t-3}}$			0.0028
			(0.015)
$\mathbf{riots_{t-1}}$	0.030	-0.057	-0.078
	(0.016)$^{+}$	(0.018)**	(0.019)***
$\mathbf{riots_{t-2}}$			-0.12
			(0.014)***
$\mathbf{riots_{t-3}}$			-0.12
			(0.015)***
Observations	403,065	403,065	382,395
Fixed effect	Parish	Parish	Parish
Time dummies	Weeks	Weeks	Weeks
Time trend	No	parish x period	parish x period
Standard errors	Conley	Conley	Conley
Estimation	OLS	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The table reports the results for the specifications in table 1, columns 1,2 and 6, but using a row-normalized weight matrix. In this matrix, elements corresponding to parishes with centroids within 10km are given a non-zero value, while all other elements are set to 0. The elements in each row of the matrix add up to 1. If parish i has n neighbors within a radius of 10km, then each element in row i corresponding to a neighbor has a value of $1/n$. As a consequence the interpretation of the coefficient on $\mathbf{W^{RN}} \times \mathbf{riots_{t-1}}$ is different: if the average number of riots in the neighborhood of parish i goes up by one in week $t-1$ (so that if there are n neighbors, the total number of riots in the neighborhood goes up by n), the expected number of riots in i goes up by an amount between 0.085 and 0.098.

Table A5: Estimates with different temporal lags

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$	(4) $\mathbf{riots_t}$	(5) $\mathbf{riots_t}$
$\mathbf{W \times riots_{t-1}}$	0.0029	0.0032	0.0032	0.0032	0.00072
	(0.00091)**	(0.00091)***	(0.00092)***	(0.00092)***	(0.0011)
$\mathbf{W \times riots_{t-2}}$		-0.00053	-0.00017	-0.00020	-0.0018
		(0.00053)	(0.00050)	(0.00055)	(0.00097)$^{+}$
$\mathbf{W \times riots_{t-3}}$			0.000088	0.00047	-0.0015
			(0.00055)	(0.00052)	(0.00100)
$\mathbf{W \times riots_{t-4}}$				0.000045	-0.0015
				(0.00062)	(0.00100)
$\mathbf{W \times riots_{t-5}}$					-0.0016
					(0.00098)
$\mathbf{W \times riots_{t-6}}$					-0.0018
					(0.00098)$^{+}$
$\mathbf{W \times riots_{t-7}}$					-0.0020
					(0.00100)*
$\mathbf{W \times riots_{t-8}}$					-0.0038
					(0.0011)***
$\mathbf{W \times riots_{t-9}}$					-0.00014
					(0.00055)
$\mathbf{W \times riots_{t-10}}$					-5.4e-06
					(0.00029)
$\mathbf{Riots_{t-1}}$	-0.055	-0.062	-0.076	-0.093	-0.26
	(0.018)**	(0.018)***	(0.019)***	(0.020)***	(0.029)***
$\mathbf{Riots_{t-2}}$		-0.11	-0.12	-0.13	-0.29
		(0.013)***	(0.014)***	(0.016)***	(0.027)***
$\mathbf{Riots_{t-3}}$			-0.12	-0.13	-0.30
			(0.015)***	(0.016)***	(0.028)***
$\mathbf{Riots_{t-4}}$				-0.13	-0.29
				(0.017)***	(0.028)***
$\mathbf{Riots_{t-5}}$					-0.29
					(0.028)***
$\mathbf{Riots_{t-6}}$					-0.29
					(0.027)***
$\mathbf{Riots_{t-7}}$					-0.28
					(0.027)***
$\mathbf{Riots_{t-8}}$					-0.26
					(0.027)***
$\mathbf{Riots_{t-9}}$					-0.11
					(0.017)***
$\mathbf{Riots_{t-10}}$					-0.060
					(0.010)***
Observations	403,065	392,730	382,395	372,060	310,050
Fixed effect	Parish	Parish	Parish	Parish	Parish
Time dummies	Weeks	Weeks	Weeks	Weeks	Weeks
Time trend	parish x period	parish x period	parish x period	parish x period	parish x period
Standard errors	Conley	Conley	Conley	Conley	Conley
Estimation	OLS	OLS	OLS	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The table reports specifications similar to those of table 1, column 6 but with different lags of riots in own parish and in the neighborhood.

Table A6: Diffusion (robustness)

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W \times riots_{t-1}}$	0.0026	0.0029
	(0.00094)**	(0.00091)**
$\mathbf{riots_{t-1}}$	-0.064	-0.055
	(0.018)***	(0.018)**
Observations	386,490	392,496
Fixed effect	Parish	Parish
Time dummies	Weeks	Weeks
Time trend	parish x period	parish x period
Standard errors	Conley	Conley
Estimation	OLS	OLS
Notes:	No Kent	No London

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10. Standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). The parish × period effects are constructed by interacting the parish dummies with four period dummies, each corresponding to a 10-week subset of the 40 weeks of unrest.

Table A7: Estimates with a 20km neighborhood

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$
$\mathbf{W^{20km}} \times \mathbf{riots_{t-1}}$	0.0017	0.0016	0.0018
	(0.00046)***	(0.00042)***	(0.00048)***
$\mathbf{W^{20km}} \times \mathbf{riots_{t-2}}$			-0.00050
			(0.00016)**
$\mathbf{W^{20km}} \times \mathbf{riots_{t-3}}$			0.000065
			(0.000078)
$\mathbf{riots_{t-1}}$	0.027	-0.060	0.025
	(0.016)$^+$	(0.019)**	(0.016)
$\mathbf{riots_{t-2}}$			-0.015
			(0.0063)*
$\mathbf{riots_{t-3}}$			-0.021
			(0.0053)***
Observations	403,065	403,065	382,395
Fixed effect	Parish	Parish	Parish
Time dummies	Weeks	Weeks	Weeks
Time trend	No	parish x period	parish x period
Standard errors	Conley	Conley	Conley
Estimation	OLS	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^+$ p<0.10. The table reports the results for the specifications in table 1, columns 1,2 and 6, but using a non-normalized matrix that defines as neighbors all parishes with centroids within a 20km radius.

Table A8: Fairs

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W} \times \mathbf{riots_{t\text{-}1}}$	0.0029	0.0018
	(0.00091)**	(0.00086)*
$\mathbf{riots_{t\text{-}1}}$	-0.055	-0.056
	(0.018)**	(0.018)**
$\mathbf{d}(\mathbf{fairsN_{t-1}})$	0.0029	0.0017
	(0.00085)***	(0.00074)*
$\mathbf{D}(\mathbf{fairsN_{t-1}})\times$ $\mathbf{d(riots\ near\ fair_{t\text{-}1})}$		0.023
		(0.0087)**
$\mathbf{d(riots\ near\ fair_{t\text{-}1})}$		0.016
		(0.0028)***
Observations	403,065	403,065
Fixed effect	Parish	Parish
Time dummies	Weeks	Weeks
Time trend	parish x period	parish x period
Standard errors	Conley	Conley
Estimation	OLS	OLS

Number of observations:

	$\mathbf{d}(\mathbf{fairsN_{t-1}})_i = 0$	$\mathbf{d}(\mathbf{fairsN_{t-1}})_i = 1$
$\mathbf{d(riots\ near\ fair_{t-1})}_i = 0$	310,975	51,284
$\mathbf{d(riots\ near\ fair_{t-1})}_i = 1$	35,749	5,096

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, + p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). $\mathbf{d}(\mathbf{fairsN_{t-1}})$ is a $n \times 1$ vector where element i equals 1 if at least one fair occurred within 10km of parish i's centroid in week $t-1$ and 0 otherwise, while $\mathbf{D}(\mathbf{fairsN_{t-1}})$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if at least one fair occurred within 10km of parish i's centroid in week $t-1$ and 0 otherwise. $\mathbf{d(riots\ near\ fair_{t-1})}$ is a $n \times 1$ vector where element i equals 1 if in week $t-1$ there was at least one riot within 10km of a fair that is near i. The interaction $\mathbf{D}(\mathbf{fairsN_{t-1}}) \times \mathbf{d(riots\ near\ fair_{t-1})}$ is constructed to ensure that it equals 1 only if the riots near the location of a fair refer to a fair that took place at $t-1$.

Table A9: Coach stops and newspapers

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{riots_{t\text{-}1}}$	-0.035	-0.035
	(0.022)	(0.022)
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})$	0.018	0.025
	(0.0044)***	(0.0036)***
$\mathbf{D(coachstopN)} \times \mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})$	0.0097	
	(0.0056)$^+$	
$\mathbf{D(newspaperN)} \times \mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})$		0.00034
		(0.0061)
Observations	403,065	403,065
Fixed effect	Parish	Parish
Time dummies	Weeks	Weeks
Time trend	parish x period	parish x period
Standard errors	Conley	Conley
Estimation	OLS	OLS

Number of observations:

	$\mathbf{D}(\mathbf{coachstopN})_i = 0$	$\mathbf{D}(\mathbf{coachstopN})_i = 1$
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})_i = 0$	143,953	234,587
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})_i = 1$	5,885	18,640

	$\mathbf{D}(\mathbf{newspaperN})_i = 0$	$\mathbf{D}(\mathbf{newspaperN})_i = 1$
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})_i = 0$	297,994	80,585
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t\text{-}1}})_i = 1$	18,296	6,229

Notes: Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, $^+$ p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). $\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t-1}})$ is a vector of length n where element i equals 1 if there was at least one riot within 10km of i at time $t-1$, $\mathbf{D}(\mathbf{coachstopN})$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if parish i is within 10km of a coach stop and 0 otherwise, and $\mathbf{D}(\mathbf{newspapersN})$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if parish i is within 10km of where a newspaper was published and 0 otherwise,

Table A10: Repression

VARIABLES	(1) $\mathbf{riots_t}$	
$\mathbf{d(riots_{t\text{-}1})}$	-0.0054	
	(0.025)	
$\mathbf{D(repression_{t\text{-}1})} \times \mathbf{d(riots_{t-1})}$	-0.16	
	(0.052)**	
$\mathbf{d(W \times riots_{t\text{-}1})}$	0.023	
	(0.0031)***	
$\mathbf{D(repression\ nearby_{t\text{-}1})} \times \mathbf{d(W \times riots_{t-1})}$	0.012	
	$(0.0071)^{+}$	
Observations	403,065	
Fixed effect	Parish	
Time dummies	Weeks	
Time trend	parish x period	
Standard errors	Conley	
Estimation	OLS	

Number of observations:

	$\mathbf{D(repression_{t\text{-}1})}_{(i,i)} = 0$	$\mathbf{D(repression_{t\text{-}1})}_{(i,i)} = 1$
$\mathbf{d(riots_{t\text{-}1})}_i = 0$	401,716	0
$\mathbf{d(riots_{t\text{-}1})}_i = 1$	1,118	270

	$\mathbf{D(repression\ nearby_{t\text{-}1})}_{(i,i)} = 0$	$\mathbf{D(repression\ nearby_{t\text{-}1})}_{(i,i)} = 1$
$\mathbf{d(W \times riots_{t\text{-}1})}_i = 0$	378,579	0
$\mathbf{d(W \times riots_{t\text{-}1})}_i = 1$	19,001	5,524

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). The $\mathbf{D}(.)$ are $n \times n$ matrices where diagonal elements are equal to 1 if the value of the variable for parish i was nonzero, all other elements are zero. $\mathbf{d}(.)$ are $n \times 1$ vectors of dummy variables where element i equals 1 if the variable in parenthesis had a nonzero value for parish i, and all other elements are 0. The variable $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ can only be 1 if $\mathbf{d(riots_{t\text{-}1})}_i$ is 1, and so it has the same value as the interaction $\mathbf{D(repression_{t\text{-}1})}_{(i,i)} \times \mathbf{d(riots_{t\text{-}1})}_i$. Consequently, we can only estimate the coefficient on either $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ or the interaction, but not both; in practice the variable $\mathbf{D(repression_{t\text{-}1})}_{(i,i)}$ is dropped by the estimation. The variable $\mathbf{D(repression\ nearby_{t\text{-}1})}_{(i,i)}$ is dropped by the estimation for this same reason.

Table A11: Petitions

VARIABLES	(1) $\mathbf{riots_t}$
$\mathbf{riots_{t\text{-}1}}$	-0.037
	$(0.022)^{+}$
$\mathbf{d(W} \times \mathbf{riots_{t\text{-}1}})$	0.018
	(0.0028)***
$\mathbf{D(petitions)} \times \mathbf{d(W} \times \mathbf{riots_{t\text{-}1}})$	0.032
	(0.0074)***
Observations	403,065
Fixed effect	Parish
Time dummies	Weeks
Time trend	parish x period
Standard errors	Conley
Estimation	OLS

Number of observations:

	$\mathbf{D}(\mathbf{petitions})_i = 0$	$\mathbf{D}(\mathbf{petitions})_i = 1$
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t-1}})_i = 0$	284,520	94,053
$\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t-1}})_i = 1$	19,323	5,202

Notes: Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, + p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999). $\mathbf{d}(\mathbf{W} \times \mathbf{riots_{t-1}})$ is a vector of length n where element i equals 1 if there was at least one riot within 10km of i at time $t-1$, $\mathbf{D}(\mathbf{petitions})$ is a $n \times n$ diagonal matrix where element (i, i) equals 1 if parish i is sent at least one petition to parliament in 1828-1831 and all other elements are 0.

Table A12: Fairs, large incidents only

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W \times large\ riots_{t\text{-}1}}$	0.002	0.001
	(0.001)*	(0.001)
$\mathbf{large\ riots_{t\text{-}1}}$	-0.065	-0.065
	(0.023)**	(0.023)**
$\mathbf{d}(\mathbf{fairsN_{t-1}})$	0.0022	0.0022
	(0.0008)**	(0.0007)**
$\mathbf{D}(\mathbf{fairsN_{t-1}}) \times \mathbf{d(large\ riots\ near\ fair_{t\text{-}1}})$		0.003
		(0.007)
$\mathbf{d(large\ riots\ near\ fair_{t\text{-}1}})$		0.015
		(0.003)***
Observations	403,065	403,065
Fixed effect	Parish	Parish
Time dummies	Weeks	Weeks
Time trend	parish x period	parish x period
Standard errors	Conley	Conley
Estimation	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999).

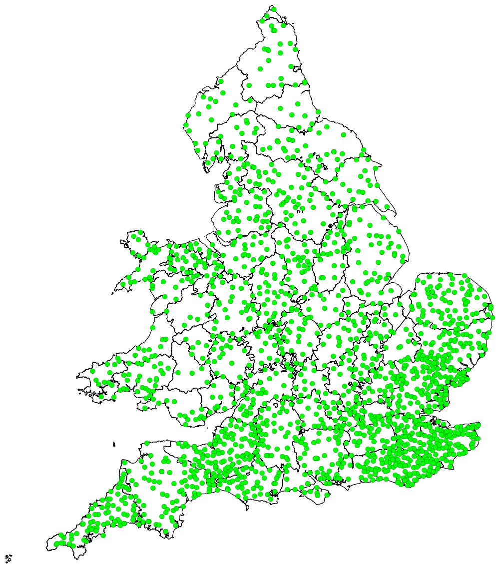
Table A13: Coach stops and newspapers, large incidents only

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{large\ riots_{t\text{-}1}}$	-0.065	-0.065
	(0.022)**	(0.022)**
$\mathbf{d(W \times large\ riots_{t\text{-}1})}$	0.031	0.042
	(0.009)***	(0.008)***
$\mathbf{D(coachstopN) \times d(W \times large\ riots_{t\text{-}1})}$	0.011	
	(0.011)	
$\mathbf{D(newspaperN) \times d(W \times large\ riots_{t\text{-}1})}$		-0.009
		(0.011)
Observations	403,065	403,065
Fixed effect	Parish	Parish
Time dummies	Weeks	Weeks
Time trend	parish x period	parish x period
Standard errors	Conley	Conley
Estimation	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.001, ** p<0.01, * p<0.05, $^{+}$ p<0.10. The standard errors are corrected for heteroskedasticity, serial autocorrelation and spatial correlation among the error terms of parishes within 10km of each other following the procedure in Conley (1999).

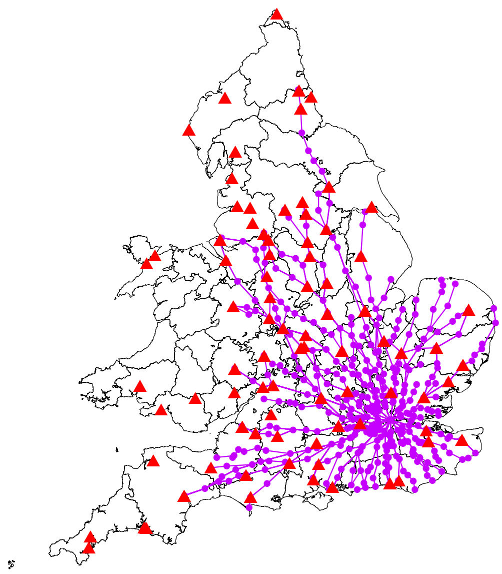
5 Maps

Figure A3: The location of fairs



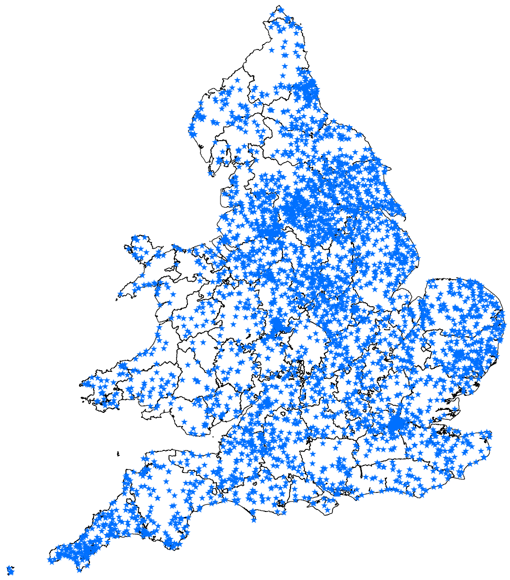
Notes: Each dot represents the location of a fair.

Figure A4: The location of coach stops and newspapers



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

Figure A5: The location of parishes that sent petitions



Notes: Each star marks the centroid of a parish that sent petitions.

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