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6773
2017

November 2017

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
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Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
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CESifo *Working Paper No. 6773*
Category 2: Public Choice

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

Abstract

Social unrest often erupts suddenly and diffuses quickly. What drives people to overcome their collective action problem and join a riot or protest, turning what is initially a small event into a widespread movement? We address this question by examining the Swing riots of 1830-31. The communication constraints of the time induced spatio-temporal variation in exposure to news about the uprising, allowing us to estimate the role of contagion in the spread of the riots. We find that local (rather than national) sources of information were central in driving contagion, and that this contagion magnified the impact that social and economic fundamentals had on riots by a factor of 2.65. Our historical data allow us to overcome a number of econometric challenges, but the Swing riots are of independent interest as well: they contributed to the passage of the Great Reform Act, a key step in Britain's institutional development.

JEL-Codes: D720, D740, O160.

Keywords: riots, diffusion, conflict, contagion, Captain Swing.

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November 7, 2017
We wish to thank Ali Hemmingway, Jay Lee, Simon Pittaway, Naomi Roba, Andriy Levitskyy and Arjun Dwesar Kumar for excellent research assistance. We are also grateful to the Cambridge Group for the History of Population and Social Structure for providing us with shape files for the maps of the ancient counties and parishes (ESRC Grant RES-000-23-1579), access to the digitized 1831 Population Census (ESRC Grant RES-000-23-1579), and access to part of the digitized 1815 poor law returns and the directory of stage coach services 1836 (Leverhulme Trust, RPG-2013-093). We thank Mauricio Rodriguez Acosta for sharing with us data on the location of police forces in England and Wales. The research was supported by the British Academy (BA grant JHAG097). We wish to thank the seminar audiences at King's College London, Essex, Oslo, Nottingham, Munich, Sheffield, Leicester, Rennes, Barcelona, Birmingham, UCL, Alghero, LSE, Oxford, Universitat Pompeu Fabra, Glasgow, York, NEPS, EPCS, Silvaplana, and EPSA for their comments. We thank Barry Eichengreen, Marco Manacorda, Andrea Tesei, Ruben Enikolopov, Antonio Ciccone, Stephane Wolton, Jordi Blanes i Vidal, Lena Gerling, Carlos Velasco, Pramila Krishnan, Elena Seghezza, Jean-Paul Azam, Nadia McCloud-Rose and James Fenske for their helpful suggestions, and Leigh Shaw-Taylor for many insightful discussions.

1 Introduction

Episodes of social unrest, including riots and protests, often erupt suddenly and diffuse quickly from one area to another, as seen in recent examples including the 1992 Los Angeles riots, the 2011 London riots and the Arab Spring revolutions in Tunisia and Egypt. What drives people to overcome their collective action problem and join a riot or a protest, turning what is initially a small event into a widespread movement? Economic theory provides two sets of explanations for why social unrest spreads. One set emphasizes social and economic *fundamentals* including poverty, unemployment and ethnicity (see, e.g., Collier and Hoeffler, 2004; Esteban and Ray, 2011; Campante and Chor, 2012b; Mitra and Ray, 2014), while the other emphasizes *contagion* (see, e.g., Granovetter, 1978; Kuran, 1989; Lohmann, 1994).[1] Riots are costly, and we may want to devise policies to prevent them; some protests, on the other hand, may seek democratic change and so are worthy of being supported. In order to formulate effective policies, we must improve our understanding of the mechanisms that drive the diffusion of riots and protests. Unfortunately, the econometric challenges involved in isolating contagion from other channels of diffusion means that there is currently little, if any, compelling evidence on the matter. In this paper, we use historical data to overcome these challenges and provide new evidence on what drives the spread of social unrest.

We focus on a specific incident of social unrest, the Swing riots of 1830-1831, and address two related issues. First, we isolate contagion from the other channels of diffusion by exploiting the time and spatial variation in exposure to riots that was generated by the communication constraints of the early 1830s. We then study the specific mechanisms the drove this contagion, paying particular attention to whether local or national information externalities were central to this process. Second, we investigate the factors that correlate with the occurrence of riots in a location, focusing on the importance of economic and social fundamentals relative to contagion. For this purpose, we collected a large dataset that tracks the evolution of the Swing riots over 40 weeks in 1830-31 across more than 10,000 parishes in England. There is a distinct advantage to focusing on riots instead of other forms of social unrest: they are often localized, and can be clearly separated into a

[1] We use diffusion to mean the overall spread of the riots (regardless of the underlying drivers), while contagion is used as a synonym for Manski (1993)'s endogenous effect: the riots that happen because other riots were taking place nearby.

number of discrete incidents that are easy to observe in the data because they happen in different places at different points in time.

Engaging with these questions using contemporary data would present a number of insurmountable challenges. There is typically little variation in terms of when people first become exposed to a riot: modern communication technologies enable news about a riot to spread very quickly and reach a large audience. Partly as a result, riots typically spread over the course of a day or two. This limited variation in terms of when different locations become exposed to the riots makes it difficult to distinguish between fundamentals and contagion. This econometric problem can be described using the terminology introduced by Manski (1993): riots can result from the endogenous effect (due to riots nearby), contextual effects (due to fundamentals in neighboring locations) or correlated effects (neighboring locations have similar fundamentals and are exposed to the same shocks). Contemporary riots data do not allow to differentiate between them. Furthermore, ease of transport today means that people can travel considerable distances to participate in a riot. This makes it difficult to link local economic and social conditions (e.g., the level of poverty) to the personal conditions of the rioters; in short, we do not know what the right fundamentals are or how to control for them.

The Swing riots allow us to address these identification problems. First, we exploit the time variation in exposure to the Swing riots to separate contagion from the contextual and correlated effects. This is possible because by modern standards, the Swing riots unfolded in slow motion, and the process was allowed to develop more or less unchecked for some time before the government intervened. However, the riots still spread fast enough for all other factors, including the fundamentals, to remain unchanged in the relevant time frame. Together, these facts suggest that we can use the spatio-temporal variation in exposure to nearby riots to estimate contagion, while dealing with the fundamentals (the contextual and correlated effects) by using parish fixed effects. In short, with our historical data we can estimate contagion because a parish's exposure to nearby riots is the only variable that changes in the relevant time period, with the changes happening at different times for different parishes. This strategy would not be feasible with cross-sectional data or with modern panel data spanning only a few days.

Second, the Swing riots predate the railroads, and the telegraph network had not yet been properly created. As a result, information had to travel over space by foot, horseback or coach in a spatially continuous way. This enables us to study different mechanisms through which information about the riots could have spread and caused contagion. In particular, we examine two local mechanisms, personal contacts and fairs, and two mechanisms that operated at the national level, access to newspapers and access to the stage coach network.

Finally, the rural and local nature of the riots and the restrictions on mobility and communication that existed at the time allow us to assign parish-specific fundamentals (size, occupational structure, wealth, connectedness, etc.) to specific riots in a way that is not possible with modern data. These fundamentals can be treated as exogenous because they predate the riots and likely remained unchanged in the 40 weeks during which the riots took place. This enables us to examine which fundamentals influenced whether a parish experienced a riot, and to quantify the importance of fundamentals *relative* to contagion.

Our focus on a specific historical event provides us with a credible identification strategy, but comes at the expense of being specific. However, the role of technological progress in triggering riots and protests is as salient today as it was in the early nineteenth century: Caprettini and Voth (2017) have recently established a causal link between the presence of labor saving machinery and the Swing riots, and so the situation of these rural farm workers in the early 1830s is not unlike that of current ex-miners in the north of England or factory workers in the American Midwest. Furthermore, the Swing riots are of substantive historical importance: at the time they made many people believe that England was on the brink of revolution (e.g., McCarthy, 1882, p. 69), and Aidt and Franck (2015) demonstrate that this fear played a critical role in the success of the Great Reform Act of 1832. This reform was a key step in the development of parliamentary democracy in the United Kingdom, and in the decades that followed led to important reforms in the support for the poor, trade policy, working conditions and local government. From this perspective, the Swing riots may have been amongst the most influential riots in English history.

Our analysis is divided into three parts. In the first part, we exploit the time and spatial variation in our data to isolate the contagion effect from correlated and contextual effects. We adopt different strategies to estimate causal coefficients, including focusing on riot onset (i.e., the first occurrence of a riot in a parish) and using instrumental variables. We find that contagion is substantial: a one unit increase in the average number of riots in a parish's neighborhood nearly triples that parish's incidence of riots in the following week. This is compelling evidence of local information externalities and suggests that local networks of personal contacts played an important role in the spread of the riots.

In the second part, we examine three possible diffusion mechanisms related to local and national information externalities. We find evidence that in the weeks following a fair, parishes near its location experienced a much stronger contagion effect than those that were farther away. This is further evidence that local information externalities mattered: the fairs helped to spread information about the riots, working as local information hubs and facilitating coordination. To study the importance of national information externalities, we look at whether locations near places that published a local or regional newspaper (which amongst other things reprinted what appeared in the London newspapers) or near coach stops (mostly on routes to London) responded to information shocks differently than other parishes. The evidence for the role of national information externalities is mixed.

In the third part, we study the cross-sectional (spatial) variation in the total riots that took place in a parish throughout the 40 weeks of the uprising. This cross-sectional analysis allows us to evaluate the relative importance of contagion (the total number of riots in the vicinity of a parish) and parish-specific, time-invariant fundamentals. We consider three groups of observable fundamentals related to demographic and economic conditions, to the connectedness of the parish to the outside world, and to repression by the authorities. We find that parishes with many agricultural families and with many traders, craftsmen, professionals and individuals who frequently petitioned parliament, experienced more riots. This is consistent with the view held by some historians (e.g., Charlesworth, 1979) that the presence in the same parish of many rural poor and a vibrant middle class was conducive to riots, since the former could provide the manpower while the latter could provide the organizational skills to overcome the collective action problem. We also find strong evidence of contagion. Combining these results, we find that contagion magnified the impact of a change in a parish-level fundamental by a factor of 2.65, showing that contagion was the primary driver of the spatial diffusion of the Swing riots.

The rest of this paper is organized as follows. Section 2 provides a brief overview of the literature on protest and riots and places our analysis in context of that work. Section 3 introduces the historical background to the Swing riots. Section 4 discusses the data. Section 5 presents the main results from the spatio-temporal analysis of the data. Section 6 explores several mechanisms through which the riots may have diffused. Section 7 presents the results from our cross-sectional analysis. Section 8 offers some concluding remarks, while the data appendix details the data sources. The supplementary material at the end of the paper reports additional estimation results.

2 Related literature

Our paper contributes to the vast literature on social conflict, of which rioting is one particular manifestation. Broadly speaking, theoretical work in this area can be divided into two strands. The first emphasizes the role of economic, political and social fundamentals in producing the conditions for social conflict. Low income and poverty, and in particular negative income shocks, can lower the opportunity cost of participation (Collier and Hoeffler, 2004; Miguel et al., 2004; Dorsch and Maarek, 2015; Aidt and Leon, 2016), and an abundant supply of underemployed young people can further increase the likelihood of conflict (Urdal, 2006; Campante and Chor, 2012a,b). Polarized societies with a small number of distinct but internally homogeneous groups are also more prone to social conflict (Esteban and Ray, 1999; Passarelli and Tabellini, 2017). Ethnicity often contributes to this by fostering between-group differences (Fearon and Laitin, 2003; Montalvo and Reynal-Querol, 2005; Esteban and Ray, 2011; Esteban et al., 2012; Mitra and Ray, 2014; Iyer and Shrivastava, 2016). In short, this strand of the literature considers that economic and social fundamentals, through their effect on each individual's cost-benefit calculations, are the root cause of social conflict.

The second strand of the literature emphasizes contagion, bandwagon effects and information cascades, downplaying the role of fundamentals. The key insight is that individual choices are interdependent: an individual's costs and benefits of participating in a riot depend critically on how many other individuals participate. The seminal model by Granovetter (1978) conceptualizes this idea by assuming that individuals have different thresholds defining how many others must participate before they too decide to join. An individual's decision to participate can trigger a bandwagon effect where "instigators" draw more reluctant "respectable citizens" into participating. Kuran (1989) uses this logic to explain revolutions and Lohmann (1994) extends the logic in her theory of information cascades. Barbera and Jackson (2016) points out that *public* demonstrations and riots are essential for this process: unlike information sharing on social media, which is effectively cheap talk, demonstrations and riots are costly signals that help convince individuals that the likelihood of success is sufficiently high to make it worthwhile for them to participate. All these models share the common feature that conflict can be contagious and that small shocks can trigger waves of riots.

Empirical work has also focused on exploring how fundamentals and contagion can explain riots.[2] It is, however, difficult to distinguish clearly between the two, particularly in contexts where information travels fast over large distances. DiPasquale and Glaeser (1998), for example, shows that individual characteristics or fundamentals (e.g. the opportunity cost of time) as well as social conditions (e.g. ethnic heterogeneity in the area) influenced riot participation in Los Angeles in 1992, but they cannot isolate the contagion effect. We contribute to the study of the determinants of riots by quantifying the relative importance of fundamentals and contagion. With recent riot data, fast mobility makes it impossible to associate the fundamentals of a particular geographical location to the conditions of those who instigated riots in that locality. In contrast, with historical data from the early 1830s we can capture the conditions of the people living and rioting in particular locations because short-run mobility was very limited. In this way, we can estimate the effect of a large range of observable parish-level characteristics.

The theoretical literature briefly summarized above emphasizes that potential rioters learn about the costs and benefits of participation or about the likelihood of success by observing the scale of social conflict around them.[3] Empirically, this raises questions about how and through which mechanism this information is transmitted to potential rioters. In part motivated by the Arab Spring, many recent papers have emphasized the role of the internet and social media in facilitating coordination (for an overview, see Sabadello, 2012). As discussed in Little (2016), potential rioters must overcome both a political coordination and a tactical coordination problem. The political coordination problem concerns how many other citizens would be willing to participate in a risky revolt. The tactical problem concerns where, when, and how to revolt. Mass and social media and the internet can help overcome the second problem, but not necessarily the first, because information and communication technologies can spread information both about regime opposition and support. This theoretical ambiguity is reflected in empirical work. Hassanpour (2014), for

[2] There is a related literature in sociology (e.g., Andrews and Biggs, 2015).

[3] Tullock (1971) points out that participation in an uprising (riot or revolution) is motivated by private benefits and not by the public goods potentially provided if the social aims of the uprising are achieved, as these will be enjoyed regardless of whether the individual participates. It follows that learning must therefore be about the private costs or benefits of rioting.

example, shows how the Mubarak regime's shutdown of the internet and the mobile phone network during the Egyptian revolution in 2011 enhanced rather than hindered conflict by catalyzing local coordination, while Enikolopov et al. (2016) provides causal evidence that the penetration of VKontakte (the Russian equivalent to Facebook) facilitated the protests that took place in the wake of the 2011 Russian election. Acemoglu et al. (2014) also finds that activity on social media helped mobilize protesters (and helped solve the tactical coordination problem) during Egypt's Arab Spring. The Swing riots predate modern communication technologies, and because of this allow us to draw a clear distinction between local information externalities, which are either first-hand and personal within small geographical areas or through local information hubs like fairs, and national information flows transmitted with some delay through the national newspapers or along the stage coach network.

Our paper is closely related to the historiography of the Swing Riots themselves. Many prominent social historians, including Hammond and Hammond (1912), Thompson (1963), Hobsbawm and Rudé (1973), Charlesworth (1979), Tilly (1995), Bohstedt (2010), and Griffin (2012) have written about the riots, often seeing them as an uprising of oppressed agricultural laborers. In seeking an explanation for why the riots happened and for their particular geography, this research has emphasized two sets of explanations that put the spotlight on *local* factors and, although not articulated in those terms by historians, follow neatly the theoretical distinction between fundamentals and contagion. For example, Hobsbawm and Rudé (1973) and Charlesworth (1979, 1983) argue that local economic (e.g., relative deprivation and underemployment) and social (e.g., the presence of local radicals) factors were important, and that local information externalities operating through personal contacts or via markets and fairs played a key role in the diffusion of the riots. The Swing riots have recently been subject to more systematic statistical analysis. Aidt and Franck (2015) exploit spatial differences in voters' exposure to the Swing riots to establish a causal link between the riots and the success of the Great Reform Act, while Caprettini and Voth (2017) use spatial information about the location of threshing machines, which were a prime target for the riots, to establish a causal link between the presence of labor saving machinery and the riots. We add to this literature in two ways. First, unlike these studies, we explore the temporal as well as the spatial nature of the Swing riots, and this enables us to examine how the riots diffused and to isolate the contagion effect from other drivers. Secondly, while Caprettini and Voth (2017) focus on one particular fundamental factor and show how it contributed to the riots, we quantify the importance of a broad set of fundamental factors relative to contagion.

Finally, our work on the Swing riots is also related to the broader literature on the spatial contagion of violent intra- and inter-state conflict and criminal activity. The large literature on the spatio-temporal dynamics of inter-state and civil war is fundamentally concerned with the same broad issues related to fundamental factors versus contagion (see the survey by Sambanis, 2002); the same is true of the literature on the "war" between competing Mexican drug trading organizations and its escalation in 2010 (Dell, 2015; Osorio, 2015).

3 Historical background

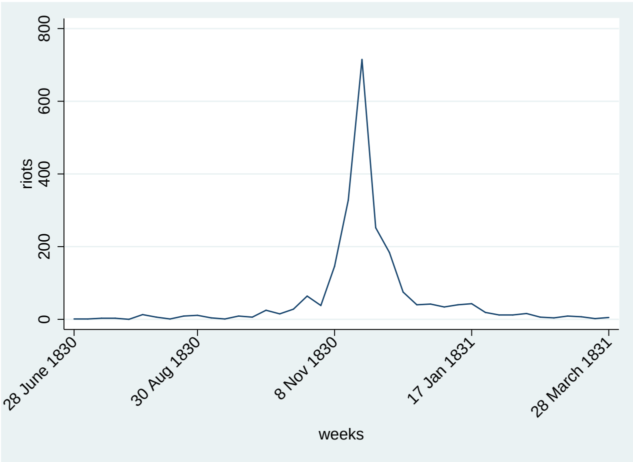
The Swing riots were a rural uprising that took place during the winter of 1830-31 mainly in the English countryside.[4] According to the riot data compiled by Hobsbawm and Rudé (1973, Appendix III) and the Family and Community Historical Research Society (Holland, 2005), almost 3000 riots took place. Figure 1 plots the number of riots per week between June 28 1830 and March 28 1831. The riots started in Kent, gained momentum in August 1830, and peaked in late November. By March 1831 they had returned to their initial low level. The map in Figure 2 shows the geography of the riots and reveals that they were concentrated in the cereal-producing areas of the south-east, in the Midlands and in East Anglia, while the dairy-producing areas in Cornwall, Wales and the north of England were less affected.

The bulk of the Swing rioters were landless farm laborers who worked for tenant farmers on daily or weekly wage contracts, supplemented by poor law subsidies from the parish in which they lived.[5] Yet, it is clear from the information about the occupations of the rioters, reported in Holland (2005), that about 16 percent of the 1270 individuals for whom

[4]The riots derived their name from the mythical Captain Swing, whose signature could be found on the threatening letters received by authority figures and others in the affected areas. Some historians (e.g. Well, 1997) have searched for a link between Captain Swing and national radical politicians, such as William Cobbett (who was accused of starting riots in Kent in October 1830 but later acquitted). However, the question of national leadership and conspiracy has been investigated and dismissed by many others (see Halévy (1923, Vol. 3), Hobsbawm and Rudé (1973, Chap. 4), Dyck (1992), Royle (2000, p. 85ff) and Jones (2009)).

[5]The agricultural economy comprised four social groups. A small group of large landowners were at the top of the social pyramid. They rented out relatively large pieces of land to between 225 and 300 thousand tenant farmers on long-term contracts who, in turn, employed about 1.5 million farm laborers on spot contracts. The fourth group consisted of craftsmen, artisans, traders and professionals who resided in the larger villages or small market towns.

Figure 1: The the number of Captain Swing riots by week, June 1830 to March 1831.



Sources: Hobsbawm and Rudé (1973, Appendix III) and Holland (2005).

occupation information is available belonged to the class of village craftsmen and traders, many of whom, unlike the farm laborers, were literate and likely played a role in organizing riots locally (e.g., Charlesworth, 1979; Well, 1997).

Despite significant out-migration to the expanding industrial centers, rural unemployment remained high throughout the 1820s, in particular outside the peak season. As a consequence, many farm laborers and their families lived in extreme poverty, a situation that was compounded by the adoption of the threshing machine, which took away much of the farm laborers' winter employment, and a failed harvest in 1829.[6] The demands of the Swing rioters were economic in nature: higher wages, separation of poor law subsidies from wage payments, and more work.[7] These demands were directed against local tenant farmers, poor law overseers, parsons, and other local parish officials.

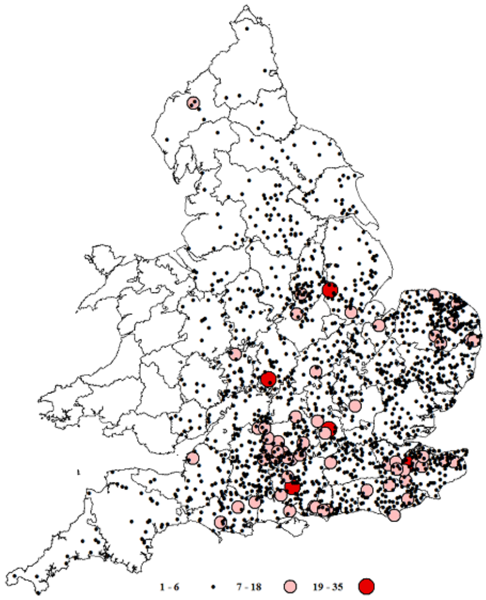
The riots took a number of different forms: burning of barns and ricks (incendiarism), destruction of threshing machines (machine breaking), robbery and forced levies of money, assaults on poor law officials, wage and tithe riots which often involved gangs of several hundred farm workers demanding higher wages or lower taxes from parish officials, and

[6]There is a significant literature that links riots and protest to adverse economic shocks induced by bad weather (e.g., Miguel et al., 2004; Chaney, 2013; Jia, 2014; Aidt and Leon, 2016; Harari and La Ferrara, 2014) or by world market price fluctuations (e.g., Dube and Vargas, 2013). While the failed harvest of 1829 arguably contributed to the uprising, any regional variation in weather conditions within the 40 week time window of the riots is unlikely to have played a role.

[7]The parish-funded poor law system provided a significant supplement to the wage income of farm laborers; it also limited out-migration, since those who moved typically lost their right to this aid (Boyer, 1990).

Figure 2: The spatial distribution of the Captain Swing Riots.

(a) All riots



Notes: The map shows the location of all recorded Swing riots. The spatial unit is a parish and a larger circle indicates more riots in a given parish.

anonymous threatening letters (Swing letters).[8] Table 1 reports the number of occurrences by type.

The authorities reacted to the riots with a combination of local concessions and repression. The local nature of the demands made by the farm laborers meant that local resolutions could be found in many cases (see, e.g., the example of Hungerford discussed in Jones (2009)). The primary responsibility for law and order rested with the landed gentry or Church of England parsons who served as magistrates or justices of the peace. They were tasked with the job of restraining and arresting the Swing rioters. However, they had very few means at their disposal, and relied on volunteers recruited from amongst local tenant farmers and other local property owners, many of whom were initially reluctant to serve. As a consequence, there were large differences in the response from the magistrates, ranging from violent repression in Hampshire and Wiltshire to accommodation in Norfolk. Nationally, the responsibility for law and order rested with the Home Office, but it too had few means at its disposal. Outside of London, about 88 Municipal Corporations had established public police forces by 1830, but the forces were small and set up to police urban, as opposed to rural, areas (Jones, 1982). The regular army was also small and

[8]We follow the historiographical literature and refer to these events as riots, acknowledging that some of them (e.g., the Swing letters) may be better described as instances of protest.

Table 1: The 12 most common types of Swing riots.

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

Source: Holland (2005).

scattered between the ports, the capital and some of the larger provincial towns. Lord Wellington's Tory government, which controlled the Home Office until November 23, 1830, reluctantly stationed some troops in or near the larger towns in the affected areas (e.g. near Canterbury and Chatham in Kent) and, in the autumn of 1830, ringed London with 7000 troops, stationed 2000 New Police in Westminster, and hastily filled the Tower of London's moat with water in order to forestall an attack (Tilly, 1995, pp. 287-88). When the Whig government assumed power on November 23, the new Home Secretary, Lord Melbourne, took more decisive action. The tangible effect was that by December 1830 about 2000 rioters had been arrested and were awaiting trial. A special commission, appointed by Lord Melbourne and sent to a number of counties in early December, sentenced many of them to death or deportation.

4 Data and Measurement

The data on the Swing riots were originally compiled by Hobsbawm and Rudé (1973, Appendix II) and substantially extended by the Family and Community Historical Research Society (Holland, 2005) and Griffin (2012). Their primary sources were London-based periodicals, Home Office documents and other official national archival reports, as well as information from local archives and newspapers. The data record the name of the parish/township/hamlet and county in which each of the recorded 2818 riots took place, the day of the riot and, for a subset of them, a short characterization of the nature of the riot and an estimate of how many individuals were involved. The riot data are almost certainly a complete record of the riots that were reported, and although it is likely that some incidents were not reported at the time, we have no reason to believe that our sample is unrepresentative. We geo-referenced each riot and aggregated the daily observations by week. The base unit of analysis is a parish-week pair, covering the 40 weeks between June 28 1830 and April 3 1831 for the 10,335 English parishes.[9] For each parish i, we used GIS software to compute the number of riots that happened in a given week in parishes with centroids within a 10km radius of parish i's centroid. In robustness checks, we consider larger neighborhoods, but the 10km radius, which corresponds to a walking distance of about 2-3 hours, is a reasonable starting point. Holland (2005, Appendix I) records the names of 1673 individuals who were arrested and trialed for participating in the riots. From this we can identify 484 riots where at least one arrest was made by the local magistrates.[10] We use this information to distinguish between riots that resulted in at least one arrest and those that did not. If we assume that the arrests were made within a week of the event, we can then use this as a measure of local law enforcement.

Data on economic and social fundamentals are drawn from the 1831 Population Census of Great Britain and a large number of other primary and secondary sources.[11] These data are recorded at the parish level and are available for up to 10,335 English parishes or townships. They do not exhibit any time variation over the course of the 40 weeks of the Swing riots. We divide the parish-specific, time-invariant economic and social fundamentals into three categories (see the Data Appendix for precise definitions of the variables and sources). The first category captures the basic demographic and economic structure of the parish. This includes census information on the area of the parish (**area**), the total population (**population**), the size of the adult male population (**males**), and the aggregate value of real property in 1815 (**wealth**). We use Caird (1852)'s division of England into four agricultural regions, along a north-south and an east-west axis, to capture differences in agricultural production. The north-south axis demarcates the eastern counties dominated by cereal production (mostly grain and wheat) from those in the west dominated by dairy farming. The east-west line, which runs through Shropshire via Leicestershire to Lincolnshire, demarcates the relatively high-wage counties in the north from the low-wage

[9] We have no information on riots in Scotland and do not have data on some of the fundamentals for Wales. We include Wales in some robustness checks.

[10] Only one arrest was made in about half the cases, but in a few as many as 40 participants were arrested. The most common offense was machine breaking, but all the main riot types were represented amongst the prosecuted cases.

[11] The information contained in the 1831 Census was collected in May 1831.

counties in the south. Based on this, we code three indicator variables – **High wage, cereal**; **Low wage, dairy**; and **Low wage, cereal** – that capture the four agricultural regions of England.[12] We measure the employment structure of a parish by recording the number of families engaged in agriculture (**families in agriculture**), the number of tenant farmers and landowners[13] (**farmers**), and the number of individuals employed in manufacturing (**manufacturing workers**), in trade and handicraft (**traders and craftsmen**), and in the professions, e.g., law, medicine or teaching (**professionals**). The dummy variable **enclosed before 1830** codes the history of enclosure of common land in the parish and equals one if the parish had enclosed prior to 1830. The enclosure of common land removed communal rights and converted it into private property (Gonner, 1912; Tate, 1978).

The second category captures how connected the parish was to the outside world. We use several proxies to capture "connectedness". First, civic groups or individuals could petition parliament directly in relationship to local or national issues. The variable **petitions**, coded from the Journals of the House of Commons, records the number of petitions between 1828 and 1831 related to the three big issues of the period: slavery, Catholic rights and parliamentary reform (House of Commons, 1831). Second, the variable **marketN** records whether a parish was within a 10km radius of a town with weekly or bi-weekly markets (Owen, 1827). Third, the variable **newspaperN** records whether a parish was within a 10km radius of a town that published a local or regional newspaper (House of Commons, 1833). Finally, the variable **coachstopN** records if a parish was within a 10km radius of a stop on the stage coach network (Bates, 1969). Being close to a regular market, to where a newspaper was published or to a coach stop, connected a parish to the outside world and enabled flows of people and information.

The third category relates to repression, which was mostly left in the hands of the local magistrates. The effectiveness with which they could respond to riots in a particular parish likely depended on whether there was an army garrison or a police force nearby. We code the variables **distance to garrison** and **policeN**; the first measures the distance to the nearest garrison (War Office, 1830), while the second is a dummy that equals 1 if the parish is located within a 10km radius of a municipal borough with a police force (Clark, 2014). Tables A1 and A2 in the Data Appendix report the descriptive statistics for these variables.

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

[13] Unfortunately, the 1831 Census includes as landowners many town dwellers with a tiny plot of land for domestic use, so this variable tends to overestimate the number of individuals who own their own land in more urban areas.

5 The spatio-temporal spread of the Swing riots

In this and the following section, we study the diffusion of the riots. We are interested in two main questions: how important was contagion and can it be separated from contextual and correlated effects? And through which mechanisms did contagion operate?

The spatio-temporal nature of the Swing riots data allow us to address the two well-known challenges to the identification of peer effects from a cross-section (Manski, 1993): we can distinguish between peer effects (endogenous and contextual) and correlated effects, and we can resolve the reflection problem and distinguish between the source of the peer effect (endogenous or contextual). This is because the time dimension allows us to model the temporal order in which the riots spread: the undeveloped state of transport and communication systems in the 1830s meant that the Swing riots spread relatively slowly, generating time variation in riot exposure (the endogenous effect) that is observable, but at the same time fast enough to render all parish-level economic and social fundamentals (the contextual and correlated effects) approximately fixed. And so our identification strategy relies on the fact that during the 40 weeks of the Swing riots these fundamentals either exhibited no time variation, and so can be picked up by parish fixed effects, or that their variation can be captured with location-specific time trends and week effects. This allows us to take out the contextual and correlated effects, leaving us only with the endogenous effect (i.e. contagion).

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, while on the right hand side, π is an $n \times 1$ vector of parish fixed effects that capture all time-invariant parish level factors. In the second term, 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 $\sum_{s=1}^{L} \beta_s \times \mathbf{W} \times \mathbf{riots_{t-s}}$, where β_s is a parameter and $\mathbf{W}$ is a $n \times n$ row-normalized weight matrix with entries corresponding to parishes with centroids within 10km being non-zero, and all other entries set to 0.[15] Therefore, parish j is considered i's neighbor if

[14] We later consider alternative time effects that allow the shocks to vary across space.

[15] The rows of the matrix add up to 1. If parish i has n neighbors within a 10km radius, then each entry in row i corresponding to a neighbor carries a weight of $1/n$. An alternative is to not row-normalize and

its centroid is within 10km of parish i's centroid, and parish i is not considered to be its own neighbor.[16] This term therefore involves time lags of the spatial lag, and captures the effect of riots in neighboring parishes at different times in the past. 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 parameter; this captures the history of riots within a parish. The term $\mathbf{u_t}$ is a $n \times 1$ vector of errors, which includes unobserved factors.

To recap, the assumption needed to isolate the contagion effect is that any correlated and contextual effects are either (i) fixed at the parish level throughout the duration of the riots, or (ii) can be picked up by the location-specific time trends or by the week effects. We estimate equation (1) with the Least Squares Dependent Variable (LSDV) estimator, adjusting the standard errors to account for spatial correlation between neighboring parishes (Conley, 1999).[17]

5.1 Baseline results

Table 2 reports estimation results for equation (1). Columns (1) and (2) show specifications with one and three temporal lags, respectively.[18] Riots in the neighborhood stop being significant after two weeks and the coefficient estimate changes sign: a riot in a neighboring parish in week $t-1$ increases the expected number of riots at time t, but one in week $t-2$ decreases it. Temporal lags of $\mathbf{riots_t}$ are all significant, with the first lag being positive, but the lags turning negative after that. This is consistent with the fact that within a parish the riots were not an explosive process: a parish experienced riots for a few weeks only, after which the riots moved on to other areas. This is also consistent with the historical context of the riots; parishes were small places and once a few riots had taken place (the threshing

focus on totals instead. Table A3 in the supplementary material reports the results with this alternative specification.

[16] Accordingly, the diagonal entries in $\mathbf{W}$ are all set to 0.

[17] This choice raises three issues. First, the spatial econometrics literature often uses a maximum likelihood estimator to avoid the bias that can arise because of the spatial lag. However, since the spatial lag in our model is not contemporaneous but enters with a one period lag, this is not an issue, and we can estimate equation (1) with the simpler LSDV estimator. Second, the presence of a lagged dependent variable can introduce Nickell bias in fixed effects models. The standard solution, which involves using a GMM estimator such as that developed by Arellano and Bond (1991), assumes that the errors are independent across the units of observation; a condition that is clearly not satisfied in our data. However, Judson and Owen (1999) show that the LSDV estimator is the best estimator in situations with more than 30 time periods, which is the case with our data. Third, the outcome variable – the number of riots in a parish in a given week – is a count variable. We show some results estimated with a Poisson model that takes this into account, but prefer the linear model as the baseline as it allows us to correct the standard errors for spatial correlation.

[18] Table A4 in the supplementary material reports specifications with up to ten temporal lags.

machines destroyed, the barns burned, or the local officials coerced into promising higher wages), there would be few, if any, targets left for new riots.[19]

The estimates of the coefficient on the first spatial lag $\mathbf{W} \times \mathbf{riots_{t-1}}$ in columns (1) and (2) capture the direct impact that an exogenous change in the average number of riots in the neighboring parishes in week $t-1$ has on riots the following week, $\mathbf{riots_t}$. They can be interpreted as marginal effects because the spatial lag enters the panel model with a one week lag, ensuring that the feedback process between parishes starts with a lag. However, the interpretation of the marginal effect is complicated by the fact that the matrix $\mathbf{W}$ is row normalized so that the coefficients relate to variation in the average number, and not in the total number, of riots nearby in the previous week. To get a sense of the magnitude of the marginal effect, consider the parish of Chilton Foliat in Wiltshire. In the third week of November 1830, it was exposed to an average of 4.4 riots in its neighborhood. This is the largest exposure of any parish throughout the uprising. This increases the expected number of riots in Chilton Foliat in the last week of November by 0.088*4.4=0.38 relative to the counter-factual of no riots nearby in the previous week. In fact, Chilton Foliat experienced 1 riot throughout the uprising (or an average of 1/40=0.025 riots per week). Compared to this, the effect of contagion is substantial: it increases the expected number of riots more than tenfold. Even in a week when there had only been, on average, one riot in the neighborhood in the previous week, the expected number of riots would more than triple.

The estimate of the coefficient on $\mathbf{W} \times \mathbf{riots_{t-1}}$ isolates the contagion effect under the maintained assumption that correlated and contextual effects are picked up by the parish and week fixed effects. This assumption would be violated if some parishes were affected by correlated shocks that varied across time *and* space. Table 2, columns (3) and (4) report results of augmented versions of equation (1) that replace the common time effects with time shocks that vary across space. First, we account for economic shocks that might differ in their impact across locations because of differences in agricultural activity. To this end, we include the interaction between the indicator for the agricultural region a parish

[19]For the effect of a riot to disappear over time, we need the coefficient on higher order lags to become smaller; the fact that they become negative indicates that the reversion to zero is very fast. In order to understand why the same pattern is expected of the spatial lag, consider a parish that suddenly finds itself surrounded by riots in its neighborhood. The probability that it experiences a riot goes up, and after the riots pass through the area the probability falls back down. If that parish experiences no riots during the period of increased riot activity in its neighborhood (a distinct possibility, since the probability of having a riot remains below 1), the change in the probability that it experiences a riot cannot be captured by the lag of the dependent variable (which in all cases will be 0). In these cases, the effect is captured by the time lags of the spatial lag, explaining why its coefficient turns negative after one week.

is located in and the week effect. For a correlated shock not to be captured, it must affect only some parishes within an agricultural region. The results are reported in column (3). We observe that the coefficient on $\mathbf{W} \times \mathbf{riots_{t-1}}$ falls from 0.088 to 0.062, but remains statistically significant at the five percent level. Second, in column (4) we include county $\times$ period dummies. We divide the uprising into four sub-periods, with the period dummies coded to correspond to each of them. This allows the economic shock to vary at the county level. The point estimate on $\mathbf{W} \times \mathbf{riots_{t-1}}$ decreases from 0.088 to 0.074 but remains very precisely estimated. Overall, the results reported in columns (3) and (4) suggest that idiosyncratic correlated shocks are not a major concern.

Columns (5) to (7) present three robustness checks. First, the riots started in Kent, and so the parishes in Kent may have differed systematically from those in the rest of the country.[20] Column (5) reports the results of a specification without these parishes, and show that our findings are not driven by the inclusion of Kent. Second, parishes close to London may have been different because of their proximity to the capital.[21] Column (6) shows that this was not the case; dropping all parishes within 20km of London has only a minimal impact on the results. These checks show that our baseline estimates are not unduly influenced by the inclusion of potentially special cases in the sample. Third, column (7) reports the results from using a fixed effects Poisson estimator that treats the number of riots in a parish as a count variable. The coefficients are different and have a different interpretation (see the table note), but the signs and significance levels are consistent with the LSDV results reported in the rest of the table.

We have also investigated the sensitivity of the contagion effect to alternative definitions of the neighborhood of a parish (reported in Table A5 in the supplementary material). The contagion effect becomes smaller as we increase the size of the neighborhood, but it remains highly statistically significant. For example, for a radius of 20km, the coefficients on the spatial lag corresponding to the specifications in Table 2, columns (1) and (2) are 0.0017 and 0.0018, respectively. This reduction is consistent with local information externalities flowing through networks of friends and family, and with the externalities created by groups of

[20]There is no consensus amongst historians as to why the riots started in Kent in August 1830 and not somewhere else. In fact, this was most likely a coincidence. The situation in Kent in August 1830 was not worse than in other cereal-producing counties in southeastern England. Hobsbawm and Rudé (1973, Chap. 4) suggest that, if anything made Kent exceptional, it was its close lines of communication with London and France.

[21]For example, Do and Campante (2009) argue that riots in the vicinity of the capital city are more threatening to the government than riots elsewhere, and so may trigger a different response.

Table 2: Panel results: The contagion effect

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$	(4) $\mathbf{riots_t}$	(5) $\mathbf{riots_t}$	(6) $\mathbf{riots_t}$	(7) $\mathbf{riots_t}$
$\mathbf{W} \times \mathbf{riots_{t-1}}$	0.085	0.088	0.062	0.074	0.072	0.087	0.397
	(0.028)***	(0.029)***	(0.026)**	(0.019)***	(0.029)**	(0.029)***	(0.116)***
$\mathbf{W} \times \mathbf{riots_{t-2}}$		-0.019	-0.031	-0.040	-0.022	-0.019	-1.719
		(0.0089)**	(0.0097)***	(0.0080)***	(0.0085)***	(0.0090)**	(0.358)***
$\mathbf{W} \times \mathbf{riots_{t-3}}$		-0.0041	-0.011	-0.041	-0.0074	-0.0037	-3.143
		(0.0062)	(0.0065)*	(0.0066)***	(0.0060)	(0.0062)	(0.538)***
$\mathbf{riots_{t-1}}$	0.030	0.029	0.028	0.028	0.024	0.029	-0.344
	(0.016)*	(0.016)*	(0.016)*	(0.016)*	(0.015)	(0.016)*	(0.034)***
$\mathbf{riots_{t-2}}$		-0.016	-0.016	-0.017	-0.019	-0.016	-0.512
		(0.0064)**	(0.0064)**	(0.0063)***	(0.0067)***	(0.0065)**	(0.063)***
$\mathbf{riots_{t-3}}$		-0.021	-0.021	-0.022	-0.022	-0.021	-0.388
		(0.0053)***	(0.0053)***	(0.0047)***	(0.0055)***	(0.0054)***	(0.072)***
Observations	403,065	382,395	382,395	382,395	366,670	372,368	382,395
R-squared	0.003	0.003	0.003	0.004	0.003	0.003	.
Fixed effects	Parish	Parish	Parish	Parish	Parish	Parish	Parish
Time effects	Weeks	Weeks	Region x week	County x period	Weeks	Weeks	Weeks
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Bootstrap (50)
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson
Note					No Kent	excl < 20km London	

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. In columns (1) to (6), the standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999). In column (3), we include the interaction between the indicator for which agricultural region of England a parish is located in and the week fixed effects. In column (4), we include the interaction between county and four period dummies, capturing each of the four sub-periods of the uprising. The coefficients in column (7) are Poisson regression coefficients. They can be interpreted as follows: if in the previous week a parish had been exposed to one more riot on average in its neighborhood, the difference in the logs of expected counts would increase by 0.397 units in the next week, while holding all other variables in the model constant.

rioters roaming the countryside becoming less important as the radius of the neighborhood expands.[22]

5.2 Reverse causality

The relative short space of time over which the riots spread, together with the observed variation in their timing, allows us to isolate the contagion effect by keeping the contextual and correlated effects constant. This, however, does not determine the direction of causality: a riot in parish i at time t can lead to a riot in parish j at time $t+1$, but then this riot might itself lead to a riot in i at $t+2$. In this section we follow two complementary strategies – focusing on riot onset and using instrumental variables – that allow us to go one step further and give our estimates a causal interpretation.

5.2.1 Riot onset

One way to address the possibility of reverse causality is to focus on the onset rather than on the incidence of riots in a parish. By definition there can be no reverse causality in this setting. We follow the literature on civil wars (e.g., Miguel et al. (2004)) and 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 impact its riot has on its neighbors.[23]

Table 3 presents estimates of the probability of onset as a function of riots in the parish's neighborhood. We cannot include lags of own riots in these estimations because their values are constant and equal to 0 by definition. To allow a direct comparison with the previous results, Table 3, column (1) shows a specification with riot incidence (the number of riots)

[22]The area that any group of rioters could cover was limited by how far the less committed rioters were willing to wander from home. Furthermore, there is no historical evidence of groups of rioters camping out overnight, which would confine them to a one-day round trip by foot (e.g., Hobsbawm and Rudé, 1973, p. 212). The most extreme example of a group of roaming rioters comes from Kintbury (located between the towns of Newbury and Hungerford) in West Berkshire, where a group of men managed to cover about 50km in one day of rioting, but this was an exception (Jones, 2009). It is unlikely that the direct effect of such roaming groups of rioters can explain much of the contagion effect we observe: the riots started by any roaming group would be confined to one day, while in the statistical model we look at riots in the neighborhood in the previous week.

[23]This is unlike the civil war literature where countries re-enter the sample once they have experienced an interval without war. We drop a parish after its first riot because we view the Swing riots as a whole as one single social movement.

Table 3: The probability of riot onset

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riotsO_t}$	(3) $\mathbf{riotsO_t}$
$\mathbf{W} \times \mathbf{riots_{t-1}}$	0.11	0.064	24.50
	(0.030)***	(0.011)***	(2.04)***
$\mathbf{W} \times \mathbf{riots_{t-2}}$	-0.032	-0.0025	21.91
	(0.0087)***	(0.0037)	(2.60)***
$\mathbf{W} \times \mathbf{riots_{t-3}}$	-0.022	0.0027	22.12
	(0.0066)***	(0.0025)	(2.42)***
Observations	382,395	363,475	20,742
R-squared	0.002	0.002	.
Fixed effects	Parish	Parish	Parish
Week effects	Yes	Yes	Yes
Standard errors	Conley	Conley	Bootstrap (50)
Estimation	OLS	OLS	Conditional FE logit

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. In columns (1) and (2), the standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999). The vector $\mathbf{riotsO_t}$ 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, so that the parish exits the sample the period after it experiences a riot. Column (3) reports conditional fixed effects logit coefficients. There is a significant drop in observations in column (3) relative to column (2) because parishes that experience no riots are dropped.

as the dependent variable but without any lags of own riots. Column (2) reports the results from a linear probability model of riot onset with parish and week fixed effects. We observe that the point estimate on $\mathbf{W} \times \mathbf{riots_{t-1}}$ is roughly half that in column (1). This suggests that feedback from parish i back to itself through neighboring parishes may be of some importance. The coefficient in column (2) shows that a one-unit increase in the average number of riots in parish i's neighborhood increases the probability of a riot onset in parish i by 6.4 percent. As a robustness check, column (3) reports conditional fixed effect logit estimates.[24] Although the coefficients are not directly comparable, the results are consistent with those in column (2).

5.2.2 Instrumental Variables

An alternative way to address reverse causality is through an instrumental variables strategy that aims at isolating exogenous variation in riots in the neighborhood of a parish. Our strategy is based on the idea that the economic and social fundamentals of a parish affect the likelihood that riots will take place, but that their impact might vary as the diffusion

[24]This is arguably a more appropriate estimator for riot onset, but its downside is that it drops all parishes that experience no riots, considerably reducing the size of the sample.

process unfolds. In other words, as the riots diffuse, the potential for time-invariant fundamentals to trigger riots changes, and our instruments exploit this variation. Specifically, we instrument the riots that happened in week t in the 10km neighborhood of parish i with interactions between the socio-economic fundamentals in parish i's neighbors and period time dummies.[25] The observable fundamentals introduced in Section 4 are fixed throughout the riot period, but the interactions with the period dummies allow us to use them as instruments in the fixed effects panel model.

To ensure that the chosen instruments are relevant, i.e., that they can explain the occurrence of nearby riots, we test which fundamentals are significantly correlated with the cross-sectional variation in the total number of riots over the 40 weeks of the uprising (see Table 8). We find nine fundamentals that pass this test: Log **area**; **Low wage, cereal**; Log **traders and craftsmen**; Log **professionals**; Log **petitions**; Log **families in agriculture**; Log **population**; Log **males**; and **policeN**. We also need to ensure that the instruments satisfy the exclusion restriction. Because of the fixed effects, we only exploit variation over time in each fundamental's ability to predict riots in parish i's neighbors. The exclusion restriction, therefore, is that these interactions have no impact on the *increase* in riots in parish i other than through the impact they have on the *increase* in riots in parish i's neighbors. The only fundamental that plausibly satisfies this condition is Log **area**, which is essentially a geographic variable with a value that results from administrative decisions made earlier in history.[26] The value of this variable for parish i's neighbors is unlikely to have a time-varying effect on riots in parish i other than through the impact it has on those neighbors. Therefore we use the interactions between the period dummies and Log **area** as instruments.

Table 4 presents the 2SLS estimates along with standard test statistics. In column (1), we consider one spatial lag only and instrument $\mathbf{W} \times \mathbf{riots_{t-1}}$ with the interaction between

[25] We define the period dummies as follows: we split the 39 weeks that are left after we apply the lag operator (which results in the observations for the first week being dropped) into three, and define **period 1** to equal 1 for weeks 2 to 14 and 0 otherwise; and define **period 2** to equal 1 for weeks 15 to 27 and 0 otherwise. The dummy corresponding to the last 13 weeks is the omitted category.

[26] The problem with the variable **Low wage, cereal** is that it will be the same for all of the parishes that are in the same agricultural region. In these cases, the interactions violate the exclusion restriction because they impact on parish i's riots directly. The other seven fundamentals violate the exclusion restriction because they can potentially have a time-varying impact on neighboring parishes. For example, this is the case for interactions with Log **traders and craftsmen**, Log **professionals** and Log **petitions**, variables that capture the size of the middle class and the extent of civic activity. The greater these are, the greater the supply of local leaders (Charlesworth, 1979), and the incentive for these local leaders to help organize riots in neighboring parishes – independently of whether their own parishes riot – likely increases as the uprising spreads.

Table 4: Instrumental variables estimation results

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W \times riots_{t-1}}$	0.960	1.021
	(0.495)*	(0.583)*
$\mathbf{riots_{t-1}}$		-0.083
		(0.069)
Observations	402,753	402,753
Number of parishes	10,327	10,327
Fixed effects	Parish	Parish
Week effects	Yes	Yes
Standard errors	Clustered	Clustered
Estimation	2SLS	2SLS
Instrumented	$\mathbf{W \times riots_{t-1}}$	$\mathbf{W \times riots_{t-1}}$
Instruments	log area × period 1	log area × period 1
	log area × period 2	log area × period 2
F-test excluded instruments	16.87	14.95
AP Chi-sq (underid)	33.74	29.91
AP F (weak id)	16.87	14.95
KP rk LM (under id)	33.30	29.59
KP rk Wald F stat (weak id)	16.89	17.15
Hansen J stat (overid test)	0.761	0.658

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The standard errors are clustered at the parish level. The instruments for riots that took place within a 10km radius of a parish are the interactions between Log **area** and a dummy **period 1** that equals 1 during weeks 2 to 14 of the riots and 0 otherwise (the first week is dropped by the lag operation, leaving 39 weeks in total) and a dummy **period 2** that equals 1 for weeks 15 to 27 of the riots and 0 otherwise. The null hypothesis in the under-identification tests is that the endogenous regressor is under-identified. The null hypothesis of the weak identification tests is that the instruments are weak. The Hansen J test is for the exogeneity of the instrument set; the null hypothesis is that the set is valid, and so we do not want to reject.

Log **area** and two period dummies. In column (2), we add a lagged dependent variable. The coefficient on the spatial lag in both specifications is roughly ten times larger than that reported in Table 2, column (2). The p-value in column (1) is 0.053. Accordingly, an exogenous increase of one in the average number of riots in the neighborhood of parish i in week $t-1$ increases the expected number of riots in parish i in week t by between 0.96 and 1.021.

It is likely that there is a fair amount of heterogeneity in how the riots spread. In that case, the IV estimates have a local average treatment effect (LATE) interpretation: they capture the impact for those parishes that were induced to riot because of the riots their neighbors experienced as a result of their fundamentals becoming more conducive to riots as the Swing riots unfolded. If this subset of parishes was more prone to riots than the average parish, then we would expect the coefficients to be larger. This could explain why the IV estimates are more than ten times the size of those obtained with the LSDV estimator.

6 The mechanisms: Local and national information flows

The most plausible explanation for the contagion effect we have estimated is information externalities: potential rioters learned about riots elsewhere and their consequences and reacted to that information. These externalities could have operated through a number of different channels. First, information could have spread by word-of-mouth or by observing other members of the local agricultural economy; these individuals shared strong personal ties that would have made them perceive this information as being credible. In particular, information about the arrest of rioters would have sent strong signals about the risks, while the congregation of individuals at local fairs would have enabled coordination and information sharing. Second, information externalities may have been created by national sources (newspapers) or by individuals from outside the parish (travelers). The landless farm workers who constituted the backbone of the uprising were largely illiterate and so could not read the newspapers, and they had at best weak ties to the individuals traveling along the coach network. Consequently, these national information externalities had to operate through local intermediaries (e.g., local tradesmen or artisans). In this section, we examine the importance of local and national information externalities.

6.1 Local law enforcement

The Swing riots could have diffused when potential rioters in one parish learned about the consequences of riots in neighboring parishes through personal contacts (Hobsbawm and Rudé, 1973, p. 159). In particular, observing or hearing about local rioters being caught and punished by the authorities may have led potential rioters to revise their beliefs about the costs of participation, and thus changed the speed of contagion. We can test this hypothesis by making a distinction between riots that did not lead to any arrests, $\mathbf{riots_{t-1}}$ **no arrest**, and those that did, $\mathbf{riots_{t-1}}$ **arrest**. We re-estimate equation (1) with the own and spatial lag of riots decomposed in this way; Table 5 reports the results. We observe two things. First, local law enforcement and repression mattered for the riot dynamics *within* a parish, helping prevent "repeat riots" in that same parish: if a parish experienced riots that

Table 5: The role of local law enforcement

VARIABLES	(1) Riots
$\mathbf{W \times riots_{t-1}}$ **no arrest**	0.024
	(0.0032)***
$\mathbf{W \times riots_{t-1}}$ **arrest**	0.018
	(0.0055)***
$\mathbf{riots_{t-1}}$ **no arrest**	0.13
	(0.028)***
$\mathbf{riots_{t-1}}$ **arrest**	0.058
	(0.041)
Equal own lag (F test)	11.58***
Equal spatial lag (F test)	1.03
Observations	403,065
R-squared	0.006
Parish fixed effect	YES
Week fixed effects	YES
Standard errors	Conley
Estimation	OLS

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999). $\mathbf{riots_{t-1}}$ **arrest** is a dummy variable equal to 1 if at least one riot with an arrest took place in parish i in week $t-1$, and $\mathbf{W \times riots_{t-1}}$ **no arrest** is a dummy variable equal to 1 if at least one riot with an arrest took place within a 10km radius of parish i in week $t-1$. The two variables for no arrest are coded to be one if there was at least one riot but there were no arrests. The F-tests for "equal own lag" and "equal spatial lag" test the null hypothesis that the coefficients for the arrest and no arrest variables are the same.

were not repressed, the expected number of riots the following week would be significantly higher than they would have been otherwise. However, riots that led to arrests have no significant effect on riots in the parish the following week. Second, and in contrast to the effect on "repeat riots", local law enforcement did not matter for contagion: the coefficients on the spatial lags – for riots with arrests and riots without arrests – are both positive and highly significant, and we cannot reject the null that the two coefficients are the same. This suggests that the local information externalities underlying the contagion process were not related to information about local repression efforts.

6.2 Fairs as local information hubs

The many fairs that took place throughout England allowed traders, craftsmen, farmers and farm laborers from the region to congregate and trade. These fairs were the focal points for the local agricultural economy, and they likely served as local information hubs where information about recent local events was shared. Those who learned about the riots in a fair would have brought this news back to the parishes in which they lived.

To explore this possible source of contagion, we study the effect that fairs had on riots in surrounding parishes. Owen (1827) reports the location and dates of the fairs. These dates and locations were set far in advance to coincide with events in the agricultural calendar.[27] Although the location of a fair could be related to factors that were also relevant to the riots, the *timing* is plausibly exogenous and so this is what we exploit.[28] Specifically, we augment equation (1) by adding the following terms

$$\gamma \mathbf{fairsN_{t-1}} + \phi \mathbf{riotsN_{t-1}} \times \mathbf{fairsN_{t-1}}, \tag{2}$$

where $\mathbf{fairsN_{t-1}}$ is a $n \times 1$ vector where element i equals 1 if there was at least one fair within 10km of parish i's centroid in week $t-1$ and 0 otherwise, $\mathbf{riotsN_{t-1}}$ is a $n \times n$ diagonal matrix where entry (i, i) equals 1 if there was at least one riot in a parish within 10km of parish i's centroid (but excluding riots in parish i itself) and 0 otherwise, and γ and ϕ are parameters. For a parish i, the first of these terms is a dummy for whether there was a fair nearby in the previous week, and the second is the interaction of that dummy with another dummy for whether there was at least one riot in parish i's neighborhood in the previous week. This formulation divides the effect of a fair into two parts on the basis of whether riots had taken place in parish i's neighborhood the prior week. This allows us to test whether having a fair nearby had an impact on riots in areas that had *not* experienced riots recently. If that is the case, it suggests that fairs contributed to the riots by enabling coordination between participants. The interaction term between fairs and riots in the neighborhood allows us to test whether fairs served as information hubs that disseminated information about riots that had taken place nearby in the previous week.

Table 6 reports the results. Column (1) shows a specification without the interaction term. We find that the coefficient on $\mathbf{fairsN_{t-1}}$ is positive and significant. In column (2), we add the interaction between the fair dummy and the indicator for whether there were any riots in the vicinity of the parish in the previous week. We find that now only the interaction term is positive and significant. This suggests that fairs influenced the diffusion of the riots only in cases where there had already been riots in the vicinity of the parish.

[27] Unlike markets, which happened on a weekly basis, fairs were not regular. Parishes that held fairs did so only a few times a year. There is no discernible temporal or spatial pattern to when or where fairs were held, and there is no evidence of fairs being canceled as a result of the riots. Map M1 in the supplementary material shows the spatial distribution of fairs.

[28] We cannot use fairs as instruments for riots in the neighborhood because they do not satisfy the exclusion restriction that a fair must have an impact on parish i's riots only through the impact it has on parish i's neighbors. This restriction requires an assumption on the extent of the region served by the fair.

Table 6: The timing of fairs: The mechanisms of diffusion

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W} \times \mathbf{riots_{t-1}}$	0.085	0.075
	(0.028)***	(0.027)***
$\mathbf{riots_{t-1}}$	0.030	0.031
	(0.016)*	(0.016)*
$\mathbf{fairsN_{t-1}}$	0.0028	0.00091
	(0.00090)***	(0.00075)
$\mathbf{W} \times \mathbf{riots_{t-1}} \times \mathbf{fairsN_{t-1}}$		0.035
		(0.0090)***
Observations	403,065	403,065
R-squared	0.003	0.003
Fixed effects	Parish	Parish
Week effects	Yes	Yes
Standard errors	Conley	Conley
Estimation	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999). $\mathbf{fairsN_{t-1}}$ 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. $\mathbf{riotsN_{t-1}} \times \mathbf{fairsN_{t-1}}$ is a $n \times 1$ vector where entry i equals 1 if there was at least one riot within 10km of parish i's centroid *and* at least one fair within 10km of parish i's centroid. We re-estimated the specifications in columns (1) and (2) with three time lags and interactions (not reported), and the results are consistent with what is reported in this table.

This is consistent with the hypothesis that fairs served as local information hubs.[29] To understand the size of the effect estimated in column (2), suppose that in week $t-1$ at least one riot takes place in the neighborhood of parish i. In the absence of a fair in week $t-1$, the expected number of riots in parish i in week t increases by 0.075. If, on the other hand, the neighboring riot coincides with a neighboring fair in week $t-1$, the impact of this nearby riot is $0.075 + 0.035 = 0.11$. Fairs thus had a substantial impact on the magnitude of contagion.

6.3 Does national information matter?

We have found strong evidence of local information externalities, operating either through personal ties between people in neighboring parishes or through fairs, and that this had a considerable impact on contagion. However, it is also possible that national information externalities contributed to contagion; for example, information about the riots could have spread through the newspapers. In the early 1830s, national news spread more slowly and

[29]It is possible that fairs also allowed future rioters to coordinate and organize. Our results cannot rule out that fairs played both roles, but they do rule out the possibility that coordination was the only role they played.

had a more limited reach than they do today. Information and people traveled along the roads by foot, horseback or coach as the railroads were yet to be built and the telegraph was in its infancy. London was the national information hub: all major newspapers were published there, and the capital was at the center of the coach network. Access to information through these networks was not open to the farm laborers: a large fraction of the rural population was illiterate and could not read newspapers; coach travel was expensive. If national news reached the farm laborers at all it is likely that it was through village radicals (belonging to the group of local artisans, traders, etc.). These radicals may have been motivated by national news about riots to take collective action locally, or simply to pass on the information to discontented farm laborers.

We code two variables to examine the role of national information in the diffusion process. They measure two different ways in which parishes were connected to the national news grid: proximity to a local newspaper and proximity to a coach stop. First, we introduce a $n \times 1$ vector **newspaperN** where element i equals 1 if parish i was close (its centroid was within 10km) of where a local or regional newspaper was printed. At the time, local and regional newspapers often reprinted material that had previously been published in the London newspapers, and so we can think of them as spreading national news (Barker, 2000).[30] Second, we introduce a $n \times 1$ vector **coachstopN** where element i equals 1 if parish i was close (its centroid was within 10km) of a coach stop. In the early 1830s, the coach network radiated out from London and connected the rest of the country to the capital (Albert, 1972). Coaches traveled along the existing turnpike roads, making stops at pre-established locations. Being close to a coach stop would have improved a parish's access to national information originating in the London news market.[31] If newspapers or the coach network were important in spreading information about the riots, and that information triggered new riots, we would expect to see a stronger contagion effect near these locations. To test this hypothesis, we augment equation (1) with interaction terms between **newspaperN** and **coachstopN** respectively and a $n \times n$ diagonal matrix $\mathbf{riotsN_{t-1}}$ where entry (i, i) equals 1 if there was at least one riot in a parish within 10km of parish i's centroid (but excluding riots in parish i itself) in week $t - 1$, and 0 otherwise. These interaction terms capture how a parish's response to riots in its vicinity is affected by its connection to the national news grid.

[30]Map M2 in the supplementary material shows the location of the local and regional newspapers.
[31]Map M2 in the supplementary appendix shows the location of the coach stops.

Table 7, column (1) reports estimates of the effect of being close to a newspaper: we find that nearby riots have a much larger impact on the riots in a parish if that parish is close to a newspaper. To get a sense for the size of this effect, consider a parish i that has experienced no riots and has seen no riots in its vicinity. If in week $t-1$ there is on average one riot in its neighboring parishes, its expected number of riots in week t increases by 0.077 if it is not close to a newspaper; if it is near a newspaper, the expected increase in riots is 25 percent larger, $0.077 + 0.019 = 0.096$. Column (2) reports the effect of proximity to coach stops. Again, we find that parishes located near coach stops experience a much stronger contagion effect, this time about 50 percent larger. Together these results show that nearby riots have a larger impact on parishes connected to the national new grid, which is consistent with national news facilitating contagion. However, we must bear in mind that there were only 80 local or regional newspapers, and that the coach network was densest in the southeast of the country, which is also where the riots started and were most intense (for reasons unrelated to the coach network). Consequently, it is likely that the connected parishes were different from the rest. In that case, the effect of proximity to newspapers and coach stops could be capturing heterogeneity induced by some other factors.

We can probe this issue further by investigating whether important events reported in the national press had a different impact on connected and unconnected parishes. If the previous results were solely caused by unobserved heterogeneity, we would not expect this to be the case. We consider two particular events. The first is the sudden increase in the number of riots at the end of October 1830. At this point the uprising went from being a local affair in Kent and assumed national significance with numerous reports in the national press: the first report about the Swing letters, for example, appeared in the Times on 21 October 1830 under the heading "More outrages in Kent" (Times, 1830). We conjecture that the acceleration of the uprising was due disproportionally to connected parishes; this could be, for example, if local organizers had read about the events in Kent in a newspaper or heard about them at the inns and pubs along the coach network. The second event is the change in government on November 23 1830.[32] As discussed previously, the new Whig administration took a more hard-line approach to the suppression of the riots than the previous Tory government: within days of taking control of the Home Office, Lord

[32]The change in government happened without an election. The Tory party had won a plurality over the Whigs in the July 1830 election, but divisions among Tory MPs allowed Earl Grey to form a Whig government when it became clear that the Tories could not continue governing.

Table 7: National information externalities: Newspapers and coach stops

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$	(3) $\mathbf{riots_t}$	(4) $\mathbf{riots_t}$	(5) $\mathbf{riots_t}$	(6) $\mathbf{riots_t}$
$\mathbf{W} \times \mathbf{riots_{t-1}}$	0.077	0.053	0.085	0.084	0.085	0.085
	(0.027)***	(0.026)**	(0.028)***	(0.028)***	(0.028)***	(0.028)***
$\mathbf{riots_{t-1}}$	0.031	0.031	0.030	0.030	0.030	0.030
	(0.016)*	(0.016)**	(0.016)*	(0.016)*	(0.016)*	(0.016)*
$\mathbf{W} \times \mathbf{riots_{t-1}} \times \mathbf{newspaperN}$	0.019					
	(0.0055)***					
$\mathbf{W} \times \mathbf{riots_{t-1}} \times \mathbf{coachstopN}$		0.023				
		(0.0038)***				
$\mathbf{newspaperN} \times d\,(t > 25Oct1830)$			-0.00036			
			(0.0010)			
$\mathbf{coachstopN} \times d\,(t > 25Oct1830)$				0.0030		
				(0.00080)***		
$\mathbf{newspaperN} \times d\,(t > 23Nov1830)$					-0.0015	
					(0.0012)	
$\mathbf{coachstopN} \times d\,(t > 23Nov1830)$						-0.0015
						(0.00095)
Observations	403,065	403,065	403,065	403,065	403,065	403,065
R-squared	0.003	0.004	0.003	0.003	0.003	0.003
Fixed effects	Parish	Parish	Parish	Parish	Parish	Parish
Week effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley
Estimation	OLS	OLS	OLS	OLS	OLS	OLS

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999). $\mathbf{riotsN_{t-1}}$ is a $n \times n$ diagonal matrix where entry (i, i) equals 1 if there was at least one riot in a parish within 10km of parish i's centroid (but excluding riots in parish i itself) and 0 otherwise. **newspaperN** and **coachstopsN** are $n \times 1$ vectors with element i set to 1 if there was a local newspaper or coach stop in the vicinity (within 10km of the centroid) of parish i, respectively. The scalar dummy $d\,(t > 25Oct1830)$ equals 1 after October 25 1830 and zero otherwise, while the scalar dummy $d\,(t > 23Nov1830)$ equals 1 after November 23 1830 and zero otherwise.

Melbourne issued a public proclamation offering a reward of £500 for bringing rioters to justice, and sent letters to the magistrates in the counties instructing them to increase their efforts to suppress the riots. News about the change in the government's use of repression may have made some individuals less willing to organize or participate in riots.

To test this hypothesis, we augment equation (1) with interactions between **newspaperN** and **coachstopN**, respectively, and a scalar dummy variable $d\,(t > 25Oct1830)$ that equals 1 for weeks after the riot acceleration (i.e., the weeks after October 25), and with a dummy $d\,(t > 23Nov1830)$ that equals 1 after the change in government (i.e., the weeks after November 23). Table 7, columns (3) and (4) present the results for the "riot acceleration" shock while columns (5) and (6) present the results for the "change in government" shock. We find that parishes connected to the coach network played a larger role in the acceleration of the riots than unconnected ones (column (4)), but proximity to newspaper appears to play no role (column (3)). We do not find evidence of a different effect on riot activity between connected and unconnected parishes in the weeks after the Whig government assumed office; the point estimates in columns (5) and (6) are negative as expected but not statistically significant.[33] These results provide limited or at best mixed support for the hypothesis that national information, transmitted by local and regional newspapers or along the coach network, facilitated diffusion.

7 Fundamentals or contagion?

The panel analysis in Section 5 establishes that contagion, fueled mainly by local information externalities, was important for the spatio-temporal diffusion of the riots. However, it cannot establish the importance of parish-specific, time-invariant fundamentals – demographic and economic factors, factors related to the connectedness of the parish to the outside world, and factors related to repression – *relative* to contagion.[34] The Swing riots offer a unique opportunity to examine this issue. The socio-economic fundamentals of a parish measure the economic and social conditions of its inhabitants, and it would have largely been these same individuals who were responsible for the riots recorded in that parish. This is because travel at the time was slow and forms of transport other than

[33]The results are largely the same when we restrict the analysis to a three-week window before and after these news.

[34]The panel model cannot address this question because the fundamentals get absorbed into the fixed effects.

walking were not open to the agricultural laborers who were the main participants in the riots. Therefore, our historical data allow us to associate the socio-economic conditions of a parish with the circumstances of the individuals rioting in that parish, something that cannot be done with recent riots data.[35] Since the fundamentals exhibited no time variation during the 40 weeks of the uprising, we must abstract from the timing of the riots and turn our attention to the cross-sectional variation in the total number of riots experienced by different parishes during the whole duration of the uprising. This amounts to changing the unit of analysis from the parish-week to the parish, of which there were 10,335 in England. The baseline specification is

$$\mathbf{riots} = \alpha\iota + \beta_1 \times \mathbf{W} \times \mathbf{riots} + \mathbf{fundamentals} \times \gamma + \mathbf{county} \times \delta + \mathbf{u}, \tag{3}$$

where **riots** is a $n \times 1$ vector where n is the number of parishes and $\mathbf{riots}_i$ refers to the total number of riots in parish i between Monday, 28th June 1830 and Sunday, 3rd April 1831. On the right hand side, the first term includes a scalar α and a unit vector ι of length n. The second term includes the scalar β_1, the $n \times n$ row-normalized weight matrix $\mathbf{W}$ with non-zero entries corresponding to parishes with centroids within 10km of each other, and all other entries set to 0.[36] This is the spatial lag, and for a parish i it records the riots happening in parishes within 10km, capturing the contagion effect. The matrix **fundamentals** has dimension $n \times k$ where k is the number of fundamentals, with row i corresponding to the fundamentals for parish i, while γ is a vector of length k with entries corresponding to the coefficients on the fundamentals. We consider the 19 parish-specific factors, related to demographic and economic conditions, to the connectedness of the parish to the outside world, and to repression, that we introduced in section 4. The matrix **county** has dimension $n \times c$ where c is the number of counties, with element (i, j) being equal to 1 if parish i is in county j and 0 otherwise, while δ is an $c \times 1$ vector with the county fixed effects. The error is given by the $n \times 1$ vector $\mathbf{u}$. Equation (3) is a standard spatial autoregressive model. The estimation of this model requires that we address the two well-known challenges to the identification of peer effects from a cross-section (Manski, 1993): first, we need to distinguish between peer effects (contagion and contextual effects) and correlated effects, and second, we need to resolve the reflection problem and distinguish

[35]There is, for example, evidence that in the 2011 London riots individuals traveled to the riot locations, with the implication that the fundamentals in those locations did not correspond to those of the rioters.

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

between the source of the peer effect (contagion or contextual). Many important correlated effects (such as shared characteristics between clusters of parishes or exposure to common law enforcement shocks) are picked up by the county fixed effects; in section 7.2 we return to the question of how to separate contagion from the contextual effect.[37]

We conduct the analysis in three parts. First, we investigate the parish-specific correlates of the riots in the absence of contagion. Second, we estimate equation (3) restricting attention to the fundamentals that we found to be significantly correlated with the riots and address the reflection problem. Third, we use these estimates to quantify the importance of the fundamentals relative to contagion.

7.1 The parish-specific correlates of the riots

To gain a better understanding of the correlation between the parish-specific fundamentals and the total number of riots in a parish, we begin by estimating a restricted version of equation (3) with $\beta_1 = 0$. This allows us to estimate the effect of each observable fundamental in the absence of contagion and to isolate the ones that are statistically significant. Table 8 presents the results. The specification in column (1) is estimated using OLS and the standard errors are corrected for spatial correlation, while the specification in column (2) is estimated using a Poisson estimator that takes into account the count nature of our riots data.[38] Both specifications include county fixed effects so that we exploit variation in parish fundamentals relative to the within county average. The observable fundamentals can explain 17 percent of the within county spatial variation in riots (column (1)).

With respect to the individual parish-level fundamentals, we observe the following. First, larger parishes experienced more riots. The same was true for parishes located in the low wage, cereal-producing region of England, and for those with more families employed in agriculture. This is to be expected, as most Swing rioters belong to this group of landless farm workers and were concentrated in the cereal-producing areas. In contrast, we observe that the enclosure of common land before 1830, contrary to the conjecture by Hammond

[37]The fact that our "reference group" for parish i – the parishes within a 10km radius of its centroid – is defined on a spatial basis, introduces non-linearities into the specification through the weighting matrix $\mathbf{W}$. This makes it easier to separately identify the contagion and contextual effect (Brock and Durlauf, 2001; Bramoullè et al., 2009; Blume et al., 2011).

[38]In studies of conflict, the negative binomial is regularly used to account for the fact that the mean and variance of the outcome variable are usually different, as is the case in our data. However, the Poisson conditional fixed effect ML estimator that we use is robust to the violation of this restriction, making the use of a negative binomial estimator unnecessary. We implement this using the *ppml* command in Stata (see Santos Silva and Tenreyro (2006)).

Table 8: The parish-specific correlates of the riots

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

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not reported. In column (1), the standard errors are corrected for spatial correlation amongst the error terms of parishes within 10km of each other (Conley, 1999) and in column (2), which reports results from a Poisson estimator, they are clustered at the county level. The unit of observation is the parish, and **Riots** measures the total number of riots in a parish during the 40 weeks of the Swing riots. All specifications include county fixed effects. The coefficients in column (2) can be interpreted as follows: for a one unit increase in the right hand side variable, each coefficient captures the difference in the logs of expected counts.

and Hammond (1912), did not play a role.[39] We also observe that variations in property valuations (**wealth**) did not matter despite the fact that this was the tax base upon which the poor law taxes were levied.

Second, we observe that parishes near coach stops, newspapers publishers or markets did not experience more riots than other parishes in their county. These factors, therefore, did not have a direct effect on the riots, but we know from the study of local and national information externalities in section 6 that they did play a role in their diffusion. The only variable related to the connectedness of a parish to the outside world that correlates (positively) with riots is the number of petitions sent to parliament. In combination with the positive correlation between the total number of riots and the population of traders, craftsmen and professionals in a parish, this suggests that village-level radicalism may have played a role. As emphasized by Charlesworth (1979), it was the craftsmen, artisans and traders with radical sympathies and knowledge of what was going on in the wider world who possessed the organizational skills to resolve the collective action problem and mobilize the local farm laborers to riot.

Third, we observe that of the two factors related to repression – closeness to a garrison (**distance to garrison**) or to a policy force (**policeN**) – only closeness to a police force correlates with the total number of riots.[40] However, this correlation is positive; if these forces played a systematic role in repressing the uprising the coefficient should have been negative.

7.2 Fundamentals, contextual effects and contagion

The presence of a spatial lag in equation (3) implies that OLS estimates will be biased and inconsistent, since the spatial lag is mechanically correlated with the error term (Anselin, 1998). To eliminate this source of bias, we estimate the equation with the spatial 2SLS estimator developed by Kelejian and Prucha (1998). This estimator instruments the spatial lag with three vectors of variables, **fundamentals**, $\mathbf{W} \times$ **fundamentals**, $\mathbf{W^2} \times$ **fundamentals**, where $\mathbf{W}$ is the weight matrix, $\mathbf{W}^2$ is the second spatial lag, and **fundamentals** is a vector of the nine fundamentals which were found to be significant in at least one of the specifications reported in Table 8. The intransitive nature of our network,

[39]This is perhaps not surprising as Shaw-Taylor (2001) has demonstrated that in many places the poor did not enjoy communal rights prior to enclosure, and so had little to lose from the process.

[40]Map M3 in the supplementary material shows the location of the police stations and the garrisons.

Table 9: Diffusion of the Swing riots: Contextual effects and contagion

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots
W × **riots**	0.92	0.73	0.49	0.92
	(0.045)***	(0.050)***	(0.062)***	(0.037)***
Observations	10,309	10,309	10,042	10,309
Dummies	County	County	County	County
Fundamentals	No	Yes	Yes	Yes
Contextual effects	No	No	No	Yes
Standard errors	Spatial	Spatial	Clustered	Spatial
Estimation	SHAC	SHAC	Poisson	SHAC

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is the parish, and **Riots** measures the total number of riots in a parish during the 40 weeks of the Swing riots. For a parish i, **W** × **riots** refers to the average number of riots across parishes within 10km of its centroid (excluding riots that happened in i itself). The fundamentals include those that were statistically significant in at least one of the specifications reported in Table 8, column (1) or (2): Log **area**, Log **population**, **Low wage, cereal**, Log **families in agriculture**, Log **traders and craftsmen**, Log **professionals**, Log **males**, Log **petitions** and **policeN**. The coefficients in column (3) are Poisson regression coefficients, estimated using the glmmboot (glmmML) command in R. The coefficients can be interpreted as follows: for a one unit increase in the right hand side variable, each coefficient captures the difference in the logs of expected counts. Column (4) shows a specification with contextual effects. This allows the average of each of the nine fundamentals in the parishes within 10km to influence riots in parish i. Table A6 in the supplementary material reports the coefficients for these contextual effects. The SHAC estimator used to estimate the coefficients in columns (1), (2) and (4) is implemented with the sphet package in R (see Piras (2010)), using a row-normalized weight matrix where parishes within 10km (Euclidean distance) are considered neighbors. The standard errors reported in these columns are robust to heteroskedasticity and spatial correlation.

where i and j can be neighbors, j and k can be neighbors, but i and k will often not be, is a sufficient condition to ensure that this instrument set is valid and informative.[41] We use the SHAC version of this estimator, which adjusts the spatial 2SLS errors for heteroskedasticity of unknown form and for spatial autocorrelation (Kelejian and Prucha, 2007).

Table 9, columns (1) and (2) report SHAC estimates of β_1. Column (1) shows a specification without any of the fundamentals included (i.e. setting $\gamma = 0$ but including county fixed effects), while column (2) shows a specification with the nine fundamentals. Column (3) reports maximum likelihood Poisson estimation results that take into account that the left-hand side variable is a count variable. The coefficient on the spatial lag is positive and highly significant in all cases: the total number of riots in a parish are positively associated with the total number of riots nearby, showing that riots cluster in space. The fact that the point estimates on the spatial lag are relatively insensitive to whether fundamentals are included, suggests that the spatial lag and the fundamentals pick up different aspects of the data generating process.

The baseline spatial autoregressive model in equation (3) does not include spatial lags of the fundamentals. This is equivalent to assuming that parish j's fundamentals have no direct impact on the riots in parish i, ruling out contextual effects. If this assumption does not hold, e.g., because farm laborers from a deprived parish destroy threshing machines in a wealthier parish nearby, then the coefficient on the spatial lag will confound the contextual effect and contagion.[42] To address this problem, we add a set of variables to equation (3) that account for the contextual effects,

$$\mathbf{W} \times \mathbf{fundamentals} \times \rho, \tag{4}$$

where the weight matrix $\mathbf{W}$ has dimension $n \times n$ and is row-normalized so that the sum of entries in any row j adds to 1. The entries corresponding to parishes within 10km of each other are non-zero, while all other entries are set to zero. Importantly, the fact

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

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

that the weight matrix is row-normalized implies that it averages the nine fundamentals across neighboring parishes. The vector ρ has length $k = 9$ and contains the coefficients on the contextual effects. Column (4) reports the results: the coefficient on the spatial lag is unaffected and the contextual effects are mostly insignificant.[43] This suggests that contextual effects were unimportant in the diffusion of the riots, a fact that bolsters the credibility of the instrumental variables strategy adopted in Section 5.2.2.

7.3 The relative importance of fundamentals and contagion

The interpretation of the coefficients on the spatial lag and on the fundamentals is not straightforward, as they cannot be interpreted as marginal effects. To see why, consider increasing the variable $\mathbf{riots}_i$ by one unit. This has an impact on $\mathbf{riots}_j$, which in turn has an impact on $\mathbf{riots}_i$, since the latter is itself a function of the former. Consequently, in order to estimate the total impact from a one unit change in $\mathbf{riots}_i$, we need to work through the whole chain of effects. To do this, we solve equation (3) for **riots** to get

$$\mathbf{riots} = \mathbf{N}\left(\alpha\iota\right) + \mathbf{N}\left(\mathbf{fundamentals} \times \gamma\right) + \mathbf{N}\left(\mathbf{county} \times \delta\right) + \mathbf{Nu} \tag{5}$$

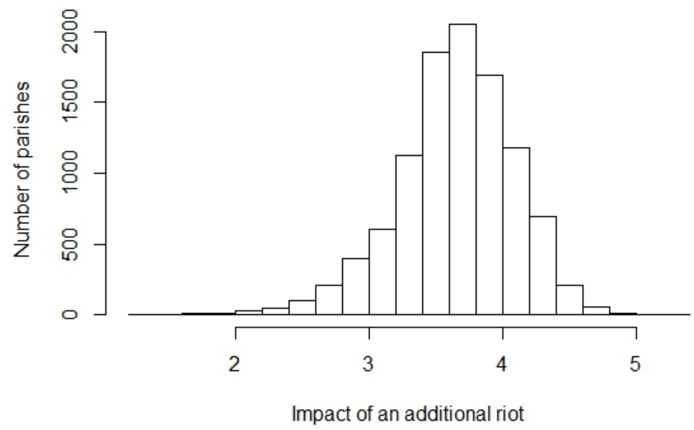
where

$$\mathbf{N} = \left(\mathbf{I} - \beta_1 \mathbf{W}\right)^{-1}. \tag{6}$$

An exogenous riot is a riot that is unexpected from the point of view of this system, and so it enters through a one unit increase in an element of the error vector, say u_i if the unexpected riot happens in parish i. This impacts on riots in parish i directly, and these riots then impact on riots in parish i' neighbors, which in turn impact on riots amongst their own neighbors including parish i, and so on. These connections are captured by the matrix $\mathbf{N}$. In particular, column i captures the impact of a shock to u_i, where $N_{j,i}$ is the total impact on parish j. Therefore, the sum of the elements in column i corresponds to the total impact of an unexpected riot in parish i (a shock to u_i). The size of this impact depends on which parish the shock hits, since connectivity affects its diffusion: different columns have different totals, corresponding to the different impact riots in different parishes have throughout the system. Figure 3 summarizes this information by presenting the distribution of column totals (based on the SHAC coefficients in Table 9, column (2)). The distribution has a mean of 3.65, a median of 3.67, and a standard deviation of 0.44, with a maximum

[43] Table A6 in the supplementary material reports the estimates for ρ.

Figure 3: Distribution of the total impact (i.e. total increase in riots) that results from a one unit increase in an element in **u**.



Note: The column totals are calculated from the SHAC estimates reported in Table 9, column (2).

impact of 5.30. To interpret these estimates, consider the average parish: the total impact of an exogenous riot in this parish is 3.65, which can be decomposed into a direct impact of 1 and an indirect impact of 2.65 due to contagion.

How does this compare to the impact of fundamentals? The fundamentals in parish i have a direct impact on riots in parish i, but they also indirectly have an impact on riots in other parishes through the feedback process just described. This indirect effect is conceptually contagion originating from parish i's riots, and so it makes sense to compare the direct impact of fundamentals to that of the contagion that follows.[44] It is possible then to imagine an exogenous one unit increase in fundamental k in a parish i and assess its effect on the total number of riots throughout the system. From equation (5), we observe that the term $\mathbf{N}\,(\mathbf{fundamentals} \times \gamma)$ captures the effect of the fundamentals. The total impact of this one unit increase is then given by $[N_{1,i} + ... + N_{n,i}] \times \gamma_k$; that is, the sum of all the entries in column i of $\mathbf{N}$ captures the total effect (as before), but now we have to multiply that effect by γ_k since this coefficient scales the unit change in that fundamental. For example, a shock to fundamental k (e.g., more petitions) in the parish with the average column total will generate a total riot effect equal to $3.65 \times \gamma_k$, of which γ_k is the direct effect and $2.65 \times \gamma_k$ is the result of contagion. In conclusion, the average effect due to contagion is 2.65 times the size of the direct effect of an exogenous change in a fundamental.

[44]In principle, it is possible that fundamentals in parish i affect riots in j directly. However, Table 9, column (4) and Table A6 in the supplementary material show that contextual effects are largely absent.

8 Conclusions

We use data from a specific episode of social unrest, the Swing riots of 1830-1831, to study how people overcome the collective action problem associated with organizing riots, and in doing so examine the mechanisms that can turn an initially small event into a major uprising. More specifically, we address two related issues. First, we isolate contagion from other social interaction effects and investigate the specific mechanisms that may have driven this contagion, focusing on the importance of local and national information externalities. Second, we examine the correlates of the riots, with a particular focus on the importance of economic and social fundamentals relative to contagion. The Swing riots provide an ideal setting in which to address these issues: they allow us to assign fundamentals to each specific riot event, and the relatively slow speed of their spread enables us to distinguish between contagion (the endogenous effect) and the fundamentals (the contextual and correlated effects). We find that contagion was more important than the fundamentals in generating riots, with the impact of a one unit increase in a fundamental magnified by a factor of 2.65 by contagion. This contagion was mostly due to local information externalities between people in neighboring parishes or between participants at local fairs.

Are the lessons from the Swing riots still valuable today in a world where mass (e.g., Yanagizawa-Drott, 2014; Crabtree et al., 2015) and social media (e.g., Hassanpour, 2014; Little, 2016; Sabadello, 2012; Lotan et al., 2011) play a leading role in all episodes of mass protest and social disorder? We believe that they are, particularly in light of recent evidence showing that online media links are largely geographic in nature and between people who live in close physical proximity to each other.[45] This work suggests that although the technology has changed, causing the diffusion process to speed up, the underlying social forces behind this process – geographically localized interactions between trusted friends and relatives – may have remained largely unchanged. Furthermore, the role of technological progress in triggering collective violence and protests is as salient today as it was at the time of the Swing riots. For example, the current situation of ex-miners in the north of England and factory workers in the American Midwest is not unlike that of the rural farm workers who were made redundant by the adoption of the threshing machine in 1830s England, as

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

demonstrated by Caprettini and Voth (2017). The Swing riots provide us with valuable lessons that can help inform our response to the most recent incarnation of these challenges.

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A Data Appendix (for publication)

This appendix provides definitions of all the variables used in the analysis and lists the sources used to construct them.

A.1 GIS datasets

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

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

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

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

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

5. Satchell, A.E.M., Shaw-Taylor, L., and Potter, E., (2016). The Cambridge Group England and Wales Town Points Dataset. This dataset was produced with funding from the Leverhulme Trust, Transport, Urbanization and Occupational Structure 1670-1911, RPG-2013-093.

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

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

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

A.2 Definition of variables and sources

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

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).

- $\mathbf{riots_{t-1}}$ **arrest** is a dummy variable equal to 1 if at least one riot with an arrest took place in parish i in week $t-1$. $\mathbf{riots_{t-1}}$ **no arrest** is coded in the same way for riots where no arrests were made. Source: Holland (2005, Appendix I). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{W} \times \mathbf{riots_{t-1}}$ **arrest** is a dummy variable equal to 1 if at least one riot with an arrest took place within a 10km radius of parish i in week $t-1$. $\mathbf{W} \times \mathbf{riots_{t-1}}$ **no arrest** is coded in the same way for the riots where no arrests were made. Source: Holland (2005, Appendix I). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- $\mathbf{fairsN_t}$ 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).

- *d(t>25Oct1830)* is a scalar dummy that equals 1 if t refers to a week that starts on or after October 25 1830 and 0 otherwise. Source: own coding.

- *d(t>23Nov1830)* is a scalar dummy that equals 1 if t refers to a week that starts on or after November 23 1830 and 0 otherwise. Source: own coding.

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

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

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

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

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

- **High wage, cereal** is an $n \times 1$ vector and **High wage, cereal**$_i$ is a dummy variable equal to one if parish i is located in the high wage cereal growing regions of England, i.e. the northeast of England. Source: Caird (1852).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

- **newspaperN** is an $n \times 1$ vector where element i is equal to one if parish i is located within a 10km radius of a town with a local or regional newspaper, and zero otherwise. House of Commons (1833) enables us to deduce the geography of the local and national newspapers. This return to the House of Commons from 1833 reports the stamp duties paid by each newspaper published in England. From the names of the newspapers, we infer the location where the 130 local and regional newspapers were published. We assume that county newspapers were published in the county seat. Source: House

Table A1: Summary statistics for the panel

	N	mean	sd	min	max
$\mathbf{Riots_{t-1}}$	413,400	0.0054	0.12	0	15
$\mathbf{Riots_{t-1}}$ **no arrest**	413,400	0.0027	0.052	0	1
$\mathbf{Riots_{t-1}}$ **arrest**	413,400	0.00081	0.028	0	1
$\mathbf{W} \times \mathbf{riots_{t-1}}$	413,400	0.0053	0.048	0	4.39
$\mathbf{W} \times \mathbf{riots_{t-1}}$ **no arrests**	413,400	0.054	0.23	0	1
$\mathbf{W} \times \mathbf{riots_{t-1}}$ **arrests**	413,400	0.018	0.13	0	1
CoachstopN	413,400	0.63	0.48	0	1
NewspaperN	413,400	0.22	0.41	0	1
$\mathbf{FairsN_{t-1}}$	405,760	0.18	0.52	0	14
log **area** × **period 1**	413,080	0.76	1.08	0	5.46
log **area** × **period 2**	413,080	0.70	1.06	0	5.46

of Commons (1833). Outside of London, all 130 local or regional newspapers were weeklies. In London there were 12 dailies (with The Times being by far the largest), seven newspapers were published three times a week, one twice a week and 37 once a week.

- Log **distance to garrison** is an $n \times 1$ vector where element i is the natural logarithm of the "as the crow flies" distance in kilometers from a parish's centroid to the nearest army or navy garrison. Source: War Office (1830).
- **policeN** is an $n \times 1$ vector where element i is equal to one if parish i is located within a 10km radius of a town with a police force. Source: Clark (2014).

Tables A1 and A2 show the summary statistics for the riot variables and the fundamentals.

Table A2: Summary statistics for the cross section

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

B Supplementary material (not for publication)

This appendix presents the additional robustness checks referred to in the main text.

Table A3: Panel estimates with a binary weight matrix

VARIABLES	(1) Riots	(2) Riots
$\mathbf{W^{NR} \times riots_{t-1}}$	0.0029	0.0030
	(0.00097)***	(0.00098)***
$\mathbf{W^{NR} \times riots_{t-2}}$		-0.00069
		(0.00035)**
$\mathbf{W^{NR} \times riots_{t-3}}$		-0.000090
		(0.00025)
$\mathbf{riots_{t-1}}$	0.032	0.031
	(0.016)**	(0.016)*
$\mathbf{riots_{t-1}}$		-0.016
		(0.0065)**
$\mathbf{riots_{t-1}}$		-0.021
		(0.0054)***
Observations	403,065	382,395
R-squared	0.002	0.003
Parish FE	Yes	Yes
Week FE	Yes	Yes
Standard errors	Conley	Conley
Estimation	OLS	OLS

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The table reports specifications similar to those of Table 2, columns (1) and (2) except that the weighting matrix is not row-normalized. Instead, the entries in the weighting matrix $\mathbf{W^{NR}}$ corresponding to parishes with centroids within 10km from each other are set to 1, while all other entries are set to 0 and the diagonal entries are all set to 0, so that a parish is not its own neighbor. This weighting system gives all riots within the neighborhood the same weight irrespective of how they relate to the underlying parish structure, so that two riots in the same parish count as much as two riots, each in a different parish. As a consequence the interpretation of the coefficient on $\mathbf{W^{NR} \times riots_{t-1}}$ is different. One extra exogenous riot (somewhere) in the neighborhood of a parish in week $t-1$ leads to an increase in the expected number of riots in that parish of between 0.0029 and 0.0030 in week t. This direct effect is relatively large, given that the unconditional expected number of riots in a parish in any given week is 0.005.

Table A4: Panel estimates with different temporal lag structures

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots
$\mathbf{W \times riots_{t-1}}$	0.085	0.088	0.088	0.088	0.087
	(0.028)***	(0.029)***	(0.029)***	(0.028)***	(0.028)***
$\mathbf{W \times riots_{t-2}}$		-0.021	-0.019	-0.019	-0.019
		(0.0092)**	(0.0090)**	(0.0091)**	(0.0094)**
$\mathbf{W \times riots_{t-3}}$			-0.0041	-0.0021	-0.0023
			(0.0063)	(0.0061)	(0.0067)
$\mathbf{W \times riots_{t-4}}$				-0.0012	0.00010
				(0.0066)	(0.0070)
$\mathbf{W \times riots_{t-5}}$					0.0016
					(0.0051)
$\mathbf{W \times riots_{t-6}}$					-0.00077
					(0.0046)
$\mathbf{W \times riots_{t-7}}$					0.0025
					(0.0049)
$\mathbf{W \times riots_{t-8}}$					0.0011
					(0.0044)
$\mathbf{W \times riots_{t-9}}$					-0.0054
					(0.0048)
$\mathbf{W \times riots_{t-10}}$					0.00088
					(0.0051)
$\mathbf{Riots_{t-1}}$	0.030	0.030	0.029	0.027	0.0095
	(0.016)*	(0.016)*	(0.016)*	(0.016)*	(0.016)
$\mathbf{Riots_{t-2}}$		-0.016	-0.016	-0.017	-0.034
		(0.0065)**	(0.0065)**	(0.0065)***	(0.0070)***
$\mathbf{Riots_{t-3}}$			-0.021	-0.021	-0.037
			(0.0054)***	(0.0054)***	(0.0064)***
$\mathbf{Riots_{t-4}}$				-0.021	-0.036
				(0.0049)***	(0.0058)***
$\mathbf{Riots_{t-5}}$					-0.040
					(0.0058)***
$\mathbf{Riots_{t-6}}$					-0.042
					(0.0052)***
$\mathbf{Riots_{t-7}}$					-0.044
					(0.0051)***
$\mathbf{Riots_{t-8}}$					-0.045
					(0.0051)***
$\mathbf{Riots_{t-9}}$					-0.044
					(0.0055)***
$\mathbf{Riots_{t-10}}$					-0.050
					(0.0055)***
Observations	403,065	392,730	382,395	372,060	310,050
Parish FE	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES
Standard errors	Conley	Conley	Conley	Conley	Conley

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The table reports specifications similar to those of Table 2, column (2) but with different lags of riots in own parish and in the neighborhood.

Table A5: Panel estimates with a 20km neighborhood

	(1) Riots	(2) Riots
$\mathbf{W^{20km}} \times \mathbf{riots_{t-1}}$	0.0017	0.0018
	(0.00046)***	(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	0.025
	(0.016)*	(0.016)
$\mathbf{riots_{t-2}}$		-0.015
		(0.0063)**
$\mathbf{riots_{t-3}}$		-0.021
		(0.0053)***
Observations	403,065	382,395
R-squared	0.004	0.005
Parish FE	Yes	Yes
Week FE	Yes	Yes
Standard errors	Conley	Conley
Estimation	OLS	OLS

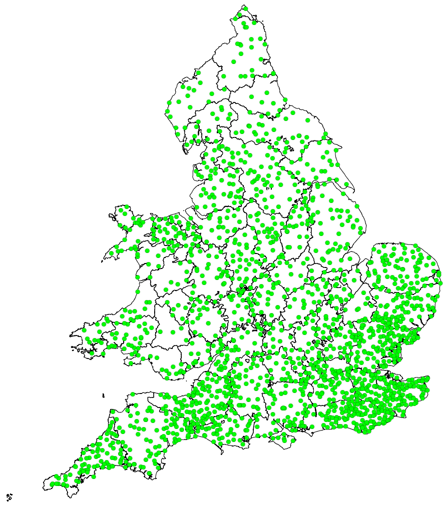
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The table reports specifications similar to those of Table 2, columns (1) and (2) except that the weighting matrix, $\mathbf{W^{20km}}$, is a row-normalized weight matrix with entries corresponding to parishes with centroids within 20km being non-zero, and all other entries set to 0. The rows of the matrix add up to 1. If parish i has n neighbors within a radium of 20km, then each entry in row i corresponding to a neighbor carries a weight of $1/n$.

Table A6: Cross-section estimates: the contextual effects

VARIABLES	(1) Riots	(2) Riots
W × **riots**	0.63	0.52
	(0.048)***	(0.068)***
W× Log **area**	-0.11	-0.66
	(0.030)***	(0.19)***
W× Log **population**	0.32	1.07
	(0.25)	(1.56)
W× **Low wage, cereal**	0.15	0.43
	(0.15)	(0.52)
W× Log **families in agriculture**	0.058	0.58
	(0.021)***	(0.16)***
W× Log **traders and craftmen**	0.029	0.074
	(0.034)	(0.26)
W×Log **professionals**	-0.040	-0.15
	(0.034)	(0.20)
W× Log **males**	-0.37	-1.39
	(0.24)	(1.71)
W× Log **petitions**	-0.089	-0.27
	(0.064)	(0.34)
W× **policeN**	-0.077	-0.075
	(0.057)	(0.22)
Observations	10,309	10,309
R-squared	0.193	
Fixed effects	County	County
Fundamentals	YES	YES
Standard errors	Conley	Cluster by par
Estimation	OLS	Poisson

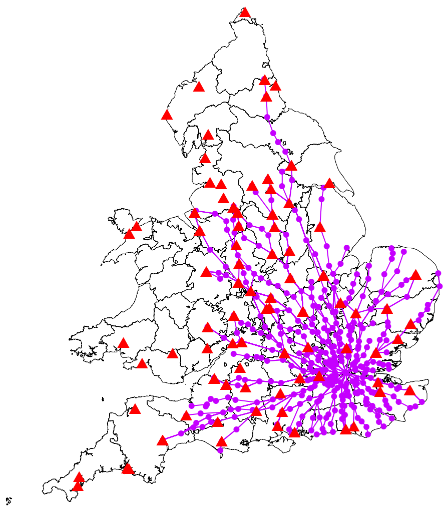
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The table reports two specifications of the spatial Durbin model with contextual effects estimated with OLS or a Poisson estimator. Both specifications include the nine fundamentals that were significant in Table 8 and county fixed effects, but to preserve space, only the contextual effects are reported. The contextual effects are defined as $\mathbf{W} \times$ **fundamentals** where the weight matrix $\mathbf{W}$ is row-normalized so that the sum of entries in any row j adds to 1. This means that it is the average of each of the nine fundamentals in the 10km neighborhood of a parish. In the table, we use the notation $\mathbf{W} \times \mathbf{fundamental_k}$ to indicate the contextual effect of fundamental k.

Figure M1: Map of the location of fairs



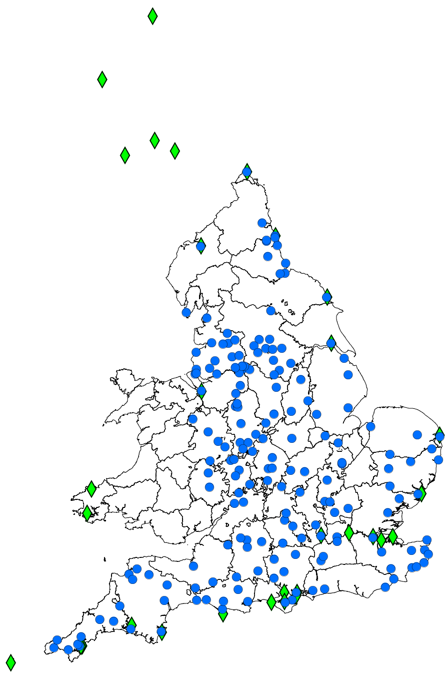
Notes: Each green dot represents a fair.

Figure M2: Map of the location of coach stops and regional newspapers



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

Figure M3: Map of the location of police stations and garrisons



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