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

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Abstract

Collective violence often erupts suddenly and diffuses quickly. We use the Swing riots in 1830-31 to provide new evidence for the mechanisms underlying this process. We study the economic and social fundamentals that made particular parishes more likely to experience riots, and examine contagion by exploiting the time and spatial variation in exposure to riots that was generated by the communication constraints of the time. Contagion was fueled by local information flows that magnified the impact of fundamentals by a factor of 6. The Swing riots involved people left behind by technological progress, an issue that remains relevant today.

JEL codes: D72; D74; O16.

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1 Introduction

Civil unrest and protests often erupt suddenly and diffuse quickly from one area to another; examples include the 1992 Los Angeles riots, the 2011 London riots and the Arab Spring revolutions in Tunisia and Egypt. Economic theory provides two types of explanations for why violence diffuses. One set of explanations 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] The econometric challenges involved in testing these alternative theories means that there is currently little, if any, systematic evidence for either of these mechanisms.

In this paper we focus on a specific incident of collective violence, the Swing riots of 1830-1831, and address two related questions.[2] First, we investigate the causes of these riots, paying particular attention to the importance of economic and social fundamentals relative to contagion. Second, we examine the specific mechanisms that may have driven the diffusion of these riots, and in particular, whether local or national sources of information were central in fueling contagion. For this purpose, we use a large dataset we collected that tracks the evolution of the Swing riots over 40 weeks in 1830-31 across more than 10,000 parishes in England. There is a distinct advantage to focusing on riots instead of other forms of collective violence: they are often localized, and can be clearly separated into a number of small and 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 presents a number of challenges. Today, ease of transport 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 funda-

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

[2] We follow the historiographical literature and refer to these events as riots acknowledging that some of them may be better described as instances of social protest.

mentals are or how to control for them. Furthermore, there is typically little variation in terms of when people first became exposed to the riots: current communication technologies enable news about the riots to spread very quickly and reach a large audience, and 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 (contagion from riots nearby), contextual effects (fundamentals in neighboring parishes) or correlated effects (neighboring parishes have similar fundamentals). Contemporary riots data do not allow us to differentiate between them.

The Swing riots allow us to address these identification problems. First, the rural and local nature of the riots and the restrictions on mobility and communication at the time allow us to assign parish-specific fundamentals (occupational structure, population density, inequality, etc.) to specific riots in a way that is not possible with more recent data.[3] These fundamentals can be treated as exogenous because they predate the riots and likely remained unchanged in the 40 week period 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 (the endogenous effect).[4]

Second, we can exploit the time variation in exposure to the Swing riots to separate contagion from the contextual and correlated effects. This is because by contemporary 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

[3]In the case of the 2011 London riots, for example, activity was centered around commercial areas, with rioters and looters traveling in from different parts of the city and coordinating through their cellular phones (e.g., Baudains et al., 2013).

[4]In addition, the Swing riots were "local" in the sense that networks of rioters and the riots themselves were contained within small geographical areas. In more recent events like the 2011 London riots, networks of friends were spread throughout the city and were brought together by social media, so that rioting often happened in areas that were far away from where the rioters lived.

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 a panel spanning only a few days.

Finally, 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 carriage in a spatially continuous way. This enables us to study different mechanisms through which information about the riots could have spread. In particular, we examine two local mechanisms, personal contact and markets and fairs, and two mechanisms that operated at the national level, access to newspapers and access to the stage coach network.

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. 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 rural farm workers made redundant by the adoption of threshing machines in the early 1830s. 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 (Maehl, 1967), and Aidt and Franck (2015) has shown that this fear played a critical role in the success of the Great Reform Act of 1832. This reform was an early and important step in the development of parliamentary democracy in the United Kingdom. From this perspective, the Swing riots may have been amongst the most influential riots in English history.[5]

Our analysis is divided into three parts. We first study the cross-sectional variation in the total riots that took place in a parish throughout the 40 weeks of the uprising, as a function of parish-level fundamentals and the total number of riots in its vicinity. We find that more urbanized areas and those with more men (which tended to be the more industrialized areas) experienced fewer riots, while the size of the population, the share

[5]This is unlike other episodes of rioting, including the 1992 Los Angeles riots and the 2011 London riots, which had little if any impact on policy.

of families in agriculture, being in a low wage cereal area (the poorest regions), the share of professionals, (wealth) inequality, the size of the middle class and being near a market town all contributed to riots. This is consistent with the view held by historians that the presence in the same parish of both rural poor and a professional and middle class was conducive to riots, since the former could provide the manpower while the latter could provide organizational skills. We also find strong evidence of contagion, a result that is robust to employing a number of different econometric strategies, including the use of a SHAC estimator that explicitly deals with endogeneity. Combining these results, we find that contagion magnified the impact of a change in a parish-level fundamental by a factor of 6, showing that contagion was the primary driver of the spatial diffusion of the Swing riots.

The advantage of the cross-sectional analysis is that it allows us to evaluate the relative importance of contagion and time-invariant fundamentals. However, this setting is not ideal for a study of diffusion, since we need time variation in order to properly observe and analyze how the riots spread. In the second part of our analysis, we exploit the time variation in our data. By doing so, we can control effectively for the correlated and contextual effects, which are plausibly fixed in the 40 weeks during which the riots took place (or can be picked up by common time effects), and thus isolate the contagion effect. We adopt a number of 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: one extra riot nearby more than doubles the baseline incidence of riots the following week. This is clear evidence that local networks of personal contacts played an important role in the spread of the riots.

Finally, we examine three possible diffusion mechanisms drawn from the historical literature on the Swing riots. 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 mattered: the fairs helped spread or organize the riots, working as local information hubs and facilitating contagion. To study the importance of national information flows, 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 flows is mixed.

In summary, we use data from a historical event, the Swing riots, to answer questions about the diffusion of collective violence that are difficult if not impossible to address with more recent data. We find that contagion was six times as important as fundamentals in driving diffusion, and that local information flows played the key role in fueling contagion.

The rest of this paper is organized as follows. Section 2 provides a brief overview of the literature on mass 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 results from the cross-sectional analysis of the riots. Section 6 presents the main results from the complete spatio-temporal analysis of the data. Section 7 explores several mechanisms through which the riots may have diffused. Section 8 offers some concluding remarks, while the appendix at the end of the paper contains the details of our data sources and additional estimation results.

2 Related literature

Our paper contributes to the vast literature on social conflict, of which rioting is one particular manifestation. Theoretical work in this area can, broadly speaking, be divided into two strands. The first strand 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). 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, therefore, has the potential to push others over their own individual-specific thresholds. This 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.[6] 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 it cannot isolate the contagion effect. Baudains et al. (2013) finds strong evidence of contagion in the 2011 London riots. The London riots spread in a contiguous way from one area to the next, interrupted by "relocation" or spatial jumps, presumably in response to law enforcement interventions.[7] In a related paper, Baudains et al. (2013) shows that the rioters were more

[6]There is a related literature in sociology (e.g., Stark et al., 1974; Andrews and Biggs, 2006, 2015).

[7]Davies et al. (2013) shows that police response time as well as the number of police officers affect the scale of rioting and how they spread.

likely to loot near transportation hubs, and to target areas with a large concentration of retail businesses. We contribute to the study of the determinants of riots by quantifying the relative importance of fundamentals and contagion. With recent riot data, fast spatial mobility often makes it impossible to associate the fundamentals of a particular geographical location to the conditions of those who instigate 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 by location-specific fundamentals; this is because short-run spatial mobility was very limited and localized. In this way, we can directly compare the effect of a large range of observable parish level characteristics, which can be taken to be constant over the 40 weeks of the riots, to the effect of having riots nearby (contagion). We find that contagion was about six times as important as the economic and social fundamentals.

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.[8] Empirically, this raises questions about how and through which mechanism this information is transmitted to potential rioters. In part motivated by the mass protests in the Arab world since 2011, 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 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

[8] 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.

coordination, while Enikolopov et al. (2016) provides causal evidence that penetration of the Russian equivalent to Facebook facilitated the wave of protest 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.

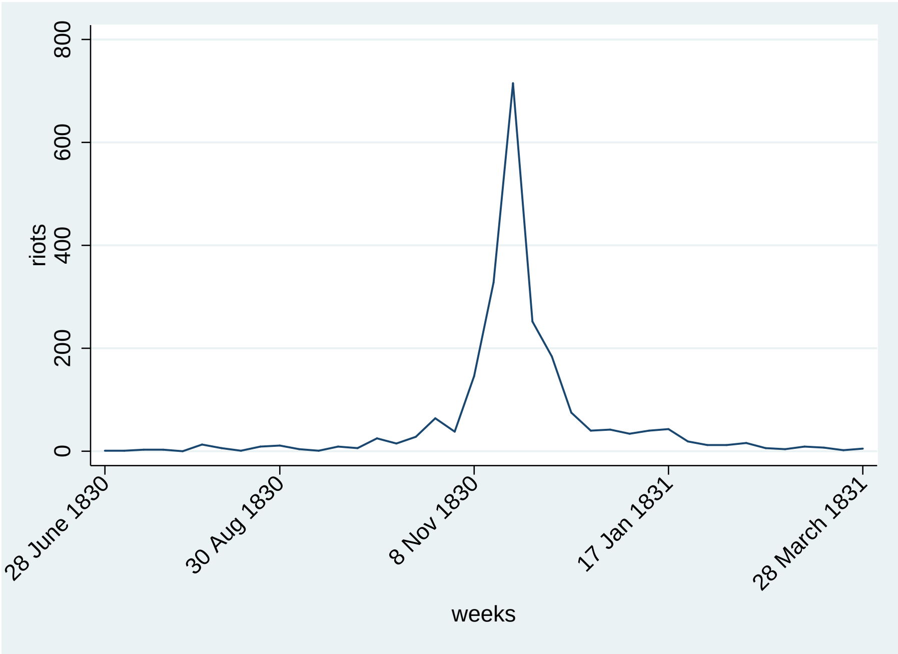
The Swing riots obviously predate modern communication technologies. Yet, precisely because of this, we can draw a clear distinction between local information flows, which are either first-hand and personal within small geographical areas or through local information hubs like fairs, and national information flows transmitted with some delay through the national newspapers or along the stage coach network. We show that information flows at the local level facilitated contagion and helped potential rioters overcome the tactical coordination problem. The evidence for the role of national information is mixed.

Our paper is, of course, closely related to the historiography of the Swing Riots themselves (e.g., Hammond and Hammond, 1912; Thompson, 1963; Hobsbawm and Rudé, 1973; Charlesworth, 1979; Tilly, 1995). We discuss this literature in section 3. 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

This section presents the relevant historical background information and discusses the historiographic work on the Swing riots.

Figure 1: The Captain Swing riots by week.



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

3.1 The Captain Swing riots

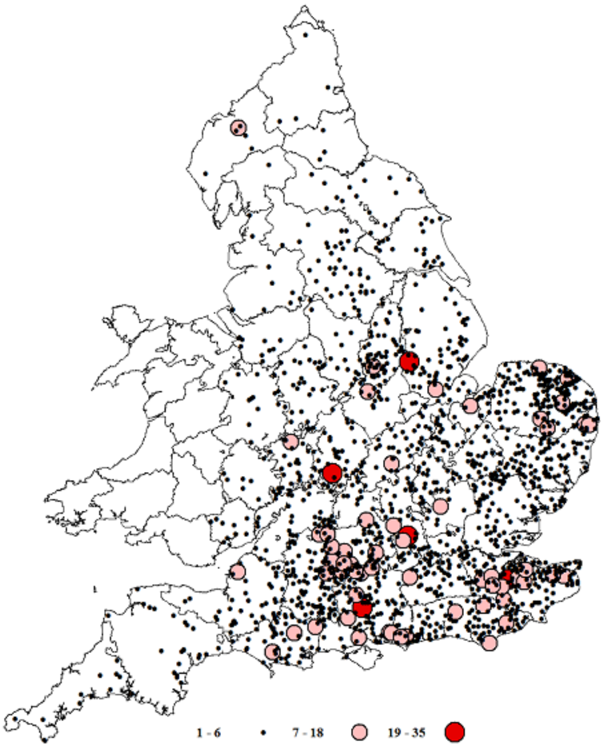
The Swing riots were a rural uprising in the English countryside that took place during the winter of 1830-31.[9] According to the riot data compiled by Hobsbawm and Rudé (1973, Appendix III) and the Family and Community Historical Research Society (Holland, 2005), almost 3000 riots took place. Figure 1 plots the number of riots per week between June 28 1830 and March 28 1831. The riots started in Kent, started to gain 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

[9]The riots derived their name from the mythical Captain Swing, whose signature could be found on the threatening letters received by authority figures in the affected areas. The word "Swing" refers to the swinging stick of the flail (Archer, 2000, p. 17).

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

(a) All riots



Notes: The map shows the location of all recorded Swing riots (a larger circle indicates more riots)

parish in which they lived.[10] 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 occupation information is available belonged to the class of village craftsmen and traders, many of whom, unlike the farm laborers, were literate.

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.[11] The demands of

[10]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 and traders who resided in the larger villages or small market towns.

[11]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

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).

the Swing rioters were economic in nature: higher wages, separation of poor law subsidies from wage payments, and more work.[12] 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 anonymous threatening letters (Swing letters). 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 in the counties 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.

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.

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

However, they had very few means at their disposal to address an uprising of the magnitude of the Swing riots. They relied on volunteers recruited from amongst local tenant farmers and other local property owners. 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 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). 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 the Lord Melbourne and sent to a number of counties in the beginning of December, sentenced many to execution or deportation.

3.2 Historiographical explanations of the riots

Many prominent social historians, including Hammond and Hammond (1912), Thompson (1963), Hobsbawm and Rudé (1973), Charlesworth (1979), Tilly (1995), and Bohstedt (2010) have written about the Swing riots, often seeing them as a concerted, purposeful uprising of oppressed agricultural laborers. However, the evidence of direct involvement of national radical leaders or other forms of national coordination is weak.[13] In seeking an explanation for why the Swing riots happened and for their particular geography, aggregate factors such as structural unemployment, general economic hardship or political tension, while playing a role, cannot provide the full answer. Historiographical research

[13] Some historians (e.g. Well, 1997) have searched for a link between 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 a national 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)). It seems clear that Cobbett exploited the riots in his newspaper (the Political Register), but that is very different from actively organizing them.

has instead 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.

With regard to local factors, historians emphasize a number of economic and social fundamentals that may have increased the likelihood that riots would take place in particular parishes.[14] There is general agreement that the type of agriculture, general deprivation, and the outside options for underemployed farm laborers all played a role. In addition, Charlesworth (1979, 1983) contends that riots were more likely in parishes with a large number of socially and economically independent individuals (artisans, craftsmen, traders and shopkeeper etc.). These parishes were more likely to host local or village radicals and thus be endowed with the organizational capital that would facilitate collective action amongst the farm laborers.

Economic and social historians have considered three different channels through which information about the riots could have spread and caused contagion. First, Hobsbawm and Rudé (1973, p. 159) emphasizes *local* information flows defined by the spatial structure of local and personal contacts between farm workers in neighboring parishes. This first-hand information may have encouraged farm laborers to imitate rioters in nearby parishes after observing that they had obtained concessions (e.g., better wages, more employment or more generous poor law subsidies), or after having learned how the local authorities had responded.

Second, the numerous small market towns scattered across the English countryside were focal points for the local agricultural economy. The weekly markets and the occasional fairs would bring locals together and serve as hubs for information exchange. Farm laborers, tenant farmers, craftsmen and traders would share local news about what was happening in their locality and bring news back with them to the villages where they lived.

Third, news in the early 1830s spread much more slowly and had a much more limited reach than they do today. Information, people and light goods traveled along the roads by

[14] There is no consensus as to why the riots started in Kent in August 1830 and not anywhere 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.

foot, horseback, cart or stagecoach in a clearly continuous spatial way. Railroads were yet to be built, while the telegraph was in its infancy. London was the national information hub, and all the major national newspapers were published there. National news spread from London to the rest of the country along the turnpike roads with the coach stops serving as local information hubs (Albert, 1972). The county seats and larger provincial towns had a local newspaper that recycled London news of local interest (Barker, 2000). Through these local hubs, national news including information about the overall scale of the riots and national repression policy would reach the village radicals who may have played a role in coordinating the riots in their localities (Charlesworth, 1979, p. 15).

4 Data and Measurement

4.1 The data

The data on the Swing riots were compiled by Hobsbawm and Rudé (1973, Appendix II) and substantially extended by the Family and Community Historical Research Society (Holland, 2005). The primary sources are London-based periodicals, Home Office documents, other official national archival reports and information from local archives and newspapers. The data record the name of the parish/township/hamlet and county in which each of the (known) 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 may have been involved. The riot data are almost certainly a complete record of the riots that were reported at the time. Undoubtedly, however, there were riots that were not reported in the press or in the official reports, but 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 the parish-week in England, covering the 40 weeks between June 28 1830 and April 3 1831.[15] 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.

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

Data on economic and social fundamentals are primarily drawn from the 1831 Population Census of Great Britain.[16] These data are recorded at the parish level and are available for 10335 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 economic and social fundamentals into five categories (the Data Appendix provides precise definitions of the variables and their sources). The first category captures the basic demographic and economic structures of the parish. This includes the variable *Log urbanization* which is a proxy for the degree of urbanization (number of houses per square acre), the variable *Share of families in agriculture* which captures how rural a parish was, and the variable *Log population* which measures the size of the parish. Caird (1852) divides England into four agricultural regions, along a north-south and an east-west axis. The north-south axis demarcates the eastern counties dominated by cereal production (mostly grain and wheat) from those in the west dominated by dairy farming. The east-west line, which runs through Shropshire via Leicestershire to Lincolnshire, demarcates the relatively high-wage counties in the north from the low-wage counties in the south. Based on this, we code three indicator variables – *High wage, cereal*; *Low wage, dairy*; and *Low wage, cereal* – that indicate in which of the four agricultural regions of England a parish is located.[17]

The second category captures the employment structure of the parish. We measure this by the share of its adult male population employed as farm workers, in manufacturing, in trade and handicraft, or as professionals, and by the share of tenant farmers or landowners. The third category captures the "riot potential" of a parish and is inspired by the historigraphical work of Hammond and Hammond (1912), Thompson (1963), Hobsbawm and Rudé (1973) and Harrison (1989). The variable *Farm labor - farmer ratio* codes the number of farm laborers – the segment of the population to which most of the Swing rioters belonged – relative to the number of tenant farmers and landowners – the segment of the population towards which most of the violence was directed.[18] The vari-

[16]The Cambridge Group for the History of Population and Social Structure has digitized the 1831 Census documents.

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

[18]Unfortunately, the 1831 Census includes as landowners many town dweller with a tiny plot of land for domestic use, and so the denominator is measured with a substantial amount of error.

able *Male share* codes the number of adult males as a percentage of the total population in the parish. The dummy variable *Enclosed before 1831* codes the history of enclosure of common land in the parish and equals one if the parish had enclosed prior to 1831. The enclosure of common land removed communal rights to a piece of land and converted it into private property (Gonner, 1912, Appendix A). This could, as stressed by Hammond and Hammond (1912), have contributed to the riots by taking away resources from the rural poor, although it appears that in many places they did not enjoy communal rights prior to enclosure (Shaw-Taylor, 2001). The variable *Inequality* codes the annual value of real property in a parish per capita (as assessed in April 1815). Since real property in most parishes was owned by a small minority of residents, we interpret this ratio as a measure of wealth inequality in the parish: places with high property values per capita would tend to be places with high wealth inequality. Our prior is that parishes with many farm workers per tenant farmer/landowner, a large number of adult males, high wealth inequality, or a history of enclosure would have a higher "riot potential" than other parishes.

The fourth category captures the degree of "village level radicalism" in the parish. We do not observe this directly but have constructed several proxies. First, the variable *Petitions 1828-31* records the total number of petitions originating from each parish and sent to the House of Commons between 1828 and 1831. It was common for civic groups to petition parliament directly in relationship to local or national issues. The three main national issues during the period leading up to the Swing riots were the abolition of slavery, rights for Catholics, and reform of the House of Commons (Cannon, 1973). Second, the variable *Log middle class* records the total number of adult males employed in trade and handicraft, the groups that Charlesworth (1979) identified as most inclined towards radicalism. Third, the variable *Near market* records whether a parish was within a 1km radius of a town with weekly or bi-weekly markets. Fourth, the variable *Near newspaper* records whether a parish was within a 10km radius of a town that published a local or regional newspaper. We expect that parishes that were politically aware and had a large middle class were also the ones that wrote petitions to parliament and hosted local radicals. Parishes close to market towns or in the vicinity of a town with a local newspaper were more effectively connected to regional and national news, potentially making village radicalism more likely.

The final 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 *Log distance to garrison* and *Near police force*; the first measures the distance to the nearest garrison, while the second is a dummy that equals 1 if the parish is located within a 1km radius of a municipal borough with a police force. In the panel analysis, we use a dummy variable to capture the effect of the shift in the national government's attitude to repression that followed from the change in government on 23rd November 1830. The Data Appendix reports the descriptive statistics for these variables.

5 The spatial pattern of the Swing riots

The Swing riots offer a unique opportunity to examine the importance of economic and social parish-level fundamentals *relative* to contagion in determining the total number of riots experienced by a parish. These fundamentals exhibited no time variation during the 40 weeks of the uprising, and so our analysis must focus on the cross-sectional variation in *total* riots.[19] These fundamentals measure the economic and social conditions of the inhabitants of a parish, and because mobility at the time was low, it would have largely been these same individuals who were responsible for the riots recorded in that parish.[20] 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 more recents riots data.[21]

The units of observation for this cross-sectional analysis are the 10,335 English parishes for which we have information on fundamentals. The baseline specification is

[19] The panel model that we introduce in Section 6 cannot address this question because the fundamentals get absorbed into the fixed effects.

[20] Travel at the time was slow, and most forms of transport were not open to the agricultural laborers who were the main participants in the riots.

[21] As we have discussed, there is evidence that in the 2011 London riots individuals traveled to the riot locations, with the implication that the fundamentals in those locations may not correspond to those of the rioters.

$$\mathbf{riots} = \alpha\iota + \beta_1 \times \mathbf{W^E} \times \mathbf{riots} + \mathbf{fundamentals} \times \gamma + \mathbf{county} \times \delta + \mathbf{u} \qquad (1)$$

where **riots** is an $n \times 1$ 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 $n \times n$ weight matrix $\mathbf{W^E}$ with entries corresponding to parishes with centroids within 10kms from each other set to 1, and all other entries set to 0.[22] This is the spatial lag, and for a parish i it gives the sum of all riots happening in parishes within 10kms, 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. **county** is an $n \times c$ matrix 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 $\mathbf{u}$.[23] Equation (1) is a standard spatial autoregressive model, except that the weighting matrix 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.[24]

5.1 Fundamentals

To gain insight into the relationship between fundamentals and the total number of riots in a parish, we first focus on a restricted version of equation (1) where $\beta_1 = 0$, which allows us to estimate the effect of the observable fundamentals in the absence of contagion. Table 2, column (1) presents the benchmark OLS estimates. The specification includes fixed effects for each of the 41 English counties, so that we exploit variation in parish characteristics relative to the within county average. The standard errors are corrected for spatial correlation amongst the error terms of parishes within 10kms of

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

[23] Table A1 in the appendix reports summary statistics.

[24] An alternative is to compute the average across neighboring parishes. This would produce a row-normalized weight matrix as in most of the literature. In our particular case, however, the total number of riots (rather than the average) is likely to be the measure that matters for contagion.

Table 2: Fundamentals and riots

VARIABLES	(1) Riots	(2) Riots
Log Urbanization	-0.070	-0.31
	(0.017)***	(0.076)***
Log population 1831	0.12	0.44
	(0.033)***	(0.20)**
Share of families in agriculture	0.0020	0.0086
	(0.00098)**	(0.0059)
High wage, cereal	0.077	0.12
	(0.040)*	(0.42)
Low wage, dairy	-0.064	-0.53
	(0.069)	(0.51)
Low wage, cereal	0.43	0.64
	(0.17)***	(0.55)
Emp. share of agricultural workers	-0.00035	0.0037
	(0.00099)	(0.0067)
Emp. share of farmers/landowner	0.0014	-0.0055
	(0.0012)	(0.0082)
Emp. share in manufacturing	-0.00072	0.0066
	(0.0012)	(0.0067)
Emp. share in trade and handicraft	0.00084	0.0054
	(0.0018)	(0.0081)
Emp. share of professionals	0.0053	0.019
	(0.0026)**	(0.024)
Farm labour - farmer ratio	-0.00012	-0.0051
	(0.0027)	(0.0075)
Male share	-0.0094	-0.082
	(0.0024)***	(0.022)***
Enclosed before 1831	0.011	0.16
	(0.023)	(0.090)*
Inequality	0.0023	-0.0017
	(0.0011)**	(0.0070)
Log middle class	0.061	0.35
	(0.026)**	(0.17)**
Near market	0.23	0.23
	(0.083)***	(0.15)
Near coach stop	0.059	-0.042
	(0.082)	(0.15)
Petitions 1828-31	0.0098	-0.0042
	(0.0081)	(0.020)
Near newspaper	-0.010	-0.0039
	(0.050)	(0.11)
Log distance to garrison	0.016	0.13
	(0.026)	(0.12)
Near police force	-0.13	0.12
	(0.100)	(0.18)
Observations	9,266	9,266
R-squared	0.167	
Dummies	County	County
Standard errors	Conley	Clustered by County
Estimation	OLS	ML Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Constants not shown. The unit of observation is the parish, and Riots refers to the total number of riots in a parish during the 40 weeks of the Swing riots. The coefficients in column 2 are estimated using the *ppml* command in Stata (see Santos Silva and Tenreyro (2006)).

each other (Conley, 1999). The observable fundamentals and county fixed effects can together explain 16.7 percent of the spatial variation in riots.

First, we find that the more urbanized areas experienced fewer riots, while more populous parishes had more riots. The share of families in agriculture had a positive impact, consistent with the fact that the Swing riots were primarily rural. Riots were also more prevalent in parishes in the low wage, cereal region relative to the omitted high wage, dairy region. Second, we look at the employment structure as measured by employment shares in different sectors, and find that only the share of professionals had a significant impact on riots. Third, two of the variables that we use to capture the "riot potential" in a parish, *Farm labor - farmer ratio* and *Male share*, do not have the expected effect: the point estimates for both are negative, with only the coefficient on the fraction of men being significant. The latter is possibly picking up the fact that parishes with many adult men were largely urban, while the Swing riots were primarily rural. Whether parishes had experienced enclosures prior to the riots did not have a significant impact on the number of riots, although the point estimate is positive as conjectured by Hammond and Hammond (1912). The last of the "riot potential" variables, *inequality*, is positive and significant. This suggests that parishes with high wealth inequality were more susceptible to riots. Fourth, we get a clear indication that "organizational capital" matters: parishes with a larger middle class or those that were close to a market town had more riots. Together with the positive correlation between the employment share of professionals and riots, this evidence is consistent with the hypothesis that village radicals played a role in resolving the collective action problem, as emphasized by Charlesworth (1979). However, this does not appear to be a result of radicals being better informed, since the number of petitions sent, being near a local newspaper, or proximity to a coach stop, all proxies for how well connected a parish was, did not make parishes more susceptible to riots. Finally, the two proxies for repression, *Log distance to garrison* and *Near police force*, are not statistically significant.

Our riots data are in the form of a count variable, and so column (2) re-estimates the restricted version of equation (1) using a Poisson estimator.[25] Although the inter-

[25] 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

pretation of the coefficients is now different, this does not fundamentally alter the set of fundamentals that mattered (from a statistical significance perspective).[26] The *Share of families in agriculture*, the *Employment share of professionals* and *Inequality* are no longer significant, while a recent experience with enclosure (*Enclosed before 1831*) now appears to have the expected positive and statistically significant effect.[27]

5.2 Fundamentals, contextual effects and contagion

The estimation of the full specification in equation (1) 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 (endogenous and contextual) and correlated effects. Second, we need to resolve the refection problem and distinguish between the source of the peer effect (endogenous or contextual). Bramoullè et al. (2009) gives conditions under which the endogenous effect – which captures riot contagion – can be identified in equations like (1), in the sense that there is enough exogenous variation to estimate the different coefficients with an appropriate estimator. Under the assumption of no correlated effects, we can identify the contextual and endogenous effects if the interaction between individuals is in networks (instead of groups). Our setting satisfies this network condition, since each parish's reference group is composed of parishes within a certain distance, inducing a directed network that is intransitive (since there is at least one parish i such that it is within 10kms of parish j, which itself is within 10kms of parish k, with parishes i and k being more than 10kms apart). If correlated effects are present, as is likely to be the case in our riots data, Corollary 1 in Bramoullè et al. (2009) establishes that identification of the endogenous effect is still possible if two additional assumptions are satisfied: the correlated effects can be picked up by a network fixed effect, and the network diameter exceeds 3. It is plausible that our setting satisfies these conditions: many of the correlated effects will be picked up by county fixed effects, which

conditional fixed effect ML estimator that we use is robust to a 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)).

[26]The coefficients in the Poisson model represent the change in the log of the expected count as each fundamental is increased by one unit, keeping the others fixed.

[27]Table A2 in the appendix presents some additional results.

Table 3: Diffusion of the Swing riots: contextual effects and contagion

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots	(7) Riots	(8) Riots
Riots neighborhood (10kms)	0.021	0.022	0.018	0.022	0.027	0.025	0.022	0.026
	(0.0044)***	(0.0035)***	(0.0037)***	(0.0036)***	(0.0031)***	(0.0032)***	(0.0036)***	(0.0018)***
Riots neighborhood (10-20kms)			0.0047					
			(0.0017)***					
Observations	10,335	9,266	9,266	9,258	9,028	8,883	9,031	9,259
R-squared	0.139	0.191	0.195	0.194	0.217	0.189	0.180	
Dummies	County	County	County	County	County	County	County	None
Fundamentals	No	Yes	Yes	Yes	Yes	Yes	Yes	Significant only
Contextual effects	No	No	No	Yes	No	No	No	No
Standard errors	Conley	Conley	Conley	Conley	Clustered	Conley	Conley	Spatial
Estimation	OLS	OLS	OLS	OLS	Poisson	OLS	OLS	SHAC
Note						excl Kent	excl < 20km London	

Notes: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is the parish, and Riots refers to the total number of riots in a parish during the 40 weeks of the Swing riots. For a parish i, Riots neighborhood (10kms) refers to the total number of riots across parishes within 10kms of its centroid (excluding riots that happened in i), while Riots neighborhood (10-20kms) refers to the total number of riots across parishes at a distance of between 10 and 20kms of its centroid. The coefficients for the fundamentals and constants are not shown but are reported in Table A3 in the appendix. The coefficients in column (5) 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, the regression coefficient captures the difference in the logs of expected counts. The coefficients in column (9) are estimated using the sphet package in R (see Piras (2010)), using a binary weight matrix where parishes within 10kms (Euclidean distance) are considered neighbors. The coefficient in column (8) should be compared to 0.029 (standard error 0.0029), which is obtained by estimating the specification in (8) using OLS and adjusting the errors following Conley (not reported to save on space). The errors reported are robust to heteroskedasticity and spatial correlation.

can be seen as proxies for the network fixed effects, and the network diameter is greater than 3.[28]

Table 3 reports the estimates of β_1 in equation (1). Column (1) presents the results of this regression without controlling for fundamentals (i.e. setting $\gamma = 0$) but including county fixed effects. The coefficient on the spatial lag is positive and highly significant: riots in a parish are positively associated with the number of riots nearby, showing that riots cluster in space. In column (2), we include the fundamentals, so that the specification corresponds to that in equation (1). The introduction of the fundamentals has no impact on the coefficient on the spatial lag, while the coefficients (and significance levels) of the fundamentals themselves are largely unchanged relative to the results in Table 2.[29] The R-squared increases from 13.9 to 19.1 when the fundamentals are added. These results suggest that the spatial lag and the fundamentals are picking up different elements of the data generating process. Column (3) introduces an additional spatial lag that counts the total number of riots taking place in parishes with centroids between 10 and 20 kilometers away from parish i's centroid. The coefficient is smaller than that on the first spatial lag, which largely remains unchanged.

The baseline spatial autoregressive model in equation (1) does not include spatial lags of the fundamentals, essentially imposing the restriction of no contextual effects. This is equivalent to assuming that parish j's fundamentals have no direct impact on the riots in parish i. Although not unreasonable given the historical context, if this assumption does not hold then the coefficient on the spatial lag will confound the contextual effect and contagion.[30] To address this problem, we add a set of variables to equation (1) that account for the contextual effects,

$$\mathbf{W^C} \times \mathbf{fundamentals} \times \rho. \tag{2}$$

[28]We revisit the issue of correlated effects in Section 6. It is worth noting that Brock and Durlauf (2001) and Blume et al. (2011) show that introducing non-linearities can, in general, help with the identification of peer effects. The definition of our reference group on a spatial basis introduces non-linearities into the specification through the weight matrix.

[29]The coefficients for the fundamentals are reported in Table A3 in the appendix.

[30]To see why, consider a parish j that is within 10kms 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.

The resulting specification is equivalent to a spatial Durbin model. The weight matrix $\mathbf{W^C}$ 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 10kms of each other are non-zero, while all other entries are set to zero. Importantly, the fact that the weight matrix is row-normalized implies that it averages the fundamentals across neighboring parishes. The vector ρ has length k and contains the coefficients on the contextual effects. Table 3, column (4) reports the results. The coefficient on the spatial lag is unaffected and the contextual effects are mostly insignificant.[31]

Column (5) reports the results using a maximum likelihood (ML) Poisson estimator that takes into account the fact that the left-hand variable is a count variable. The sign and significance of the coefficient on the spatial lag is unchanged.[32] Column (6) reports the estimate of equation (1) with the observations from the county of Kent excluded. The Swing riots began in Kent, and this specification checks that our results are not being driven by that county alone. Similarly, column (7) shows results where all observations that are within 20kms of London are dropped. In both cases, the coefficient on the spatial lag remains largely unchanged.

The presence of a spatial lag causes the OLS estimates to be biased and inconsistent, since the spatial lag is mechanically correlated with the error term (Anselin, 1998). To eliminate this source of bias, we use the spatial 2SLS estimator developed by Kelejian and Prucha (1998). This estimator instruments the spatial lag with three variables, $\{\mathbf{fundamentals}, \mathbf{M} \times \mathbf{fundamentals}, \mathbf{M^2} \times \mathbf{fundamentals}\}$, where $\mathbf{M}$ is a weight matrix of distances between parishes and $\mathbf{M}^2$ is the second spatial lag. The intransitive nature of our network, where i and j can be neighbors, j and k can be neighbors, but i and k will often not be, is a sufficient condition to ensure that this instrument set is valid and informative.[33] In column (8), we report the results for the SHAC version of this

[31]Table A4 in the appendix reports the full set of regressions with contextual effects.

[32]The estimate can be transformed into an incidence rate ratio (IRR) by using the exponential function. The IRR is 1.03 which means that a parish with one riot in its neighborhood is expected to have an incidence rate 1.03 times that of parish without a riot nearby (i.e., a 3 percent increase). However, this requires that all other variables in the model be held constant; as we discuss in Section 5.3, this assumption is not appropriate in our setting.

[33]More specifically, the exogenous variation is contained in $\mathbf{M^2} \times \mathbf{fundamentals}$, since the other two instruments are the fundamentals and the contextual effects (although in our setting the latter do not appear to be relevant). 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

estimator, which adjusts the spatial 2SLS errors for heteroskedasticity of unknown form and for spatial autocorrelation (Kelejian and Prucha, 2007).[34] We find that the coefficient on the spatial lag is largely unchanged and still highly significant.This confirms the robustness of our results by showing that the effect we found survives once we address the endogeneity problem.

5.3 The relative importance of fundamentals and contagion

The interpretation of the coefficients on the spatial lag and fundamentals is not straightforward, as they cannot be interpreted as marginal impacts. 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 (1) in terms of **riots** to get

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

where

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

An exogenous riot would be a riot that is unexpected from the point of view of this system, and so it would enter through a one unit increase in an element of the error vector, say u_i if the shock is in parish i. This would impact on i directly, i would then impact on its neighbors, who would themselves impact on their own neighbors including i, and so on. These connections are captured by the matrix $\mathbf{N}$. In particular, column i will

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.

[34]The estimates in column 8 are calculated using the sphet package in R (see Piras (2010)), using a binary weight matrix $\mathbf{M}$ where parishes within 10kms of each other (Euclidean distance) are considered neighbors. Computational constraints forced us to estimate this with only a subset of our fundamentals in a specification without county fixed effects. We included only those fundamentals that were statistically significant in previous specifications (*log urbanization*, *log population 1831*, *share of families in agriculture*, *low wage dairy*, *low wage cereal*, *employment share of professionals*, *male share*, *inequality*, *log middle class*, *near market*). The SHAC coefficient in column (8) should be compared to 0.029 (standard error 0.0029), which is obtained by estimating the specification in (8) using OLS and adjusting the errors following Conley (not reported to save on space).

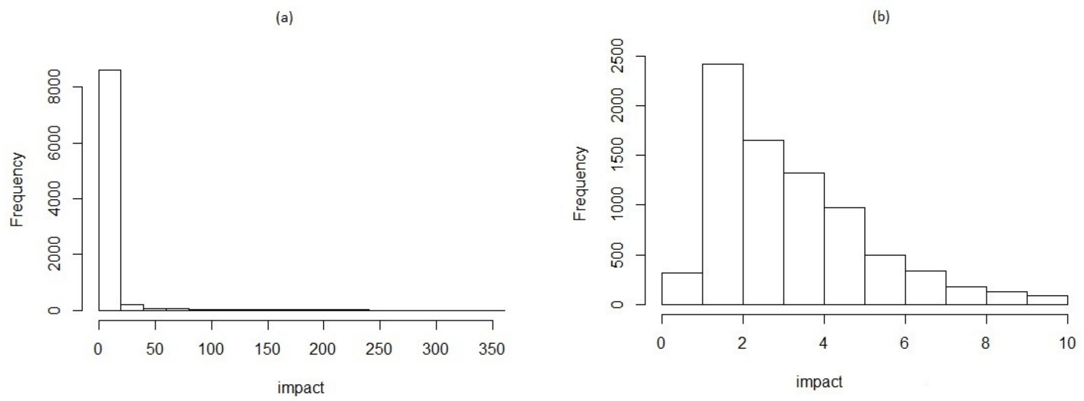


Figure 3: (a) Distribution of the total impact (i.e. total increase in riots) that results from a one unit increase in an element in $\mathbf{u}$. (b) Distribution of total impact excluding the 1,313 parishes with an impact greater than 10.

capture 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 represents the total impact of a shock to u_i. The size of this impact will depend on where the shock happens, since connectivity will affect the diffusion of the exogenous riot: different columns will likely provide different totals, corresponding to the different impact riots in different parishes would have throughout the system. We summarize this information by presenting the distribution of column totals in figure 3, which was calculated using the SHAC coefficient in table 3, column (8). The distribution has a mean of 7.14 and a standard deviation of 37.67, with a maximum impact of 340.76.[35] To interpret these estimates, consider the average parish. The total impact of an exogenous riot in this parish is 7.14, which can be decomposed into a direct impact of 1 and an indirect impact of 6.14 due to contagion.

How does this compare to the impact of fundamentals? To answer this question, consider the fundamentals in parish i. They have a direct impact on riots in 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

[35]Some column totals (1409 of the 9,259 entries) are negative because the coefficients are estimated using a linear model. In these cases, we set the impact to 0. In addition, there are 1,313 parishes with an impact of over 10, implying that the location of the exogenous riot can play a very large role in determining the size of the contagion effect.

of the contagion that follows.[36] It is possible then to imagine an exogenous one unit increase in fundamental k in a parish i and assess its effect on total riots throughout the system. From equation (3), 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 fundamental k. For example, a shock to fundamental k in the parish with the average column total will generate a total riot effect equal to $7.14 \times \gamma_k$, of which γ_k is the direct effect and $6.14 \times \gamma_k$ is the result of contagion. In conclusion, the average effect due to contagion is about six times the size of the direct effect of an exogenous change in a fundamental.

6 The spatio-temporal pattern of the Swing riots

The cross-sectional specification in Section 5 does not properly address the question of diffusion, since it eliminates the time dimension and imposes simultaneity on a process that is inherently dynamic. The time aggregation makes it difficult to think about causality because all of the information about when the riots happened is lost. Furthermore, correlated effects may still be an issue, since it is possible that there were unobservable fundamentals that were common across a subset of neighboring parishes within a county (e.g. common unobservable shocks that affected some but not all parishes in a county). These unobservables will necessarily sit in the error term and potentially bias our coefficients.

In this section we take full advantage of the spatio-temporal nature of our Swing riots data to address these issues. The time dimension allows us to model the temporal order in which the riots spread, and in the process provides us with a plausible way to distinguish between contagion (the endogenous effect) and the correlated and contextual effects. We do so by exploiting the fact that the undeveloped state of transport and communication in the 1830s meant that the Swing riots spread relatively slowly, generating time vari-

[36] In principle, it is possible that fundamentals in parish i affect riots in j directly. However, column (4) in Table 3 and the full results in table A4 in the appendix show that these contextual effects are largely absent.

ation that is observable, but at the same time fast enough to render all fundamentals approximately fixed. Our identification strategy then relies on the fact that during the 40 weeks during which the Swing riots took place, the correlated and contextual effects were fixed and so can be picked up by parish fixed effects.[37] This removes the contextual and correlated effects, leaving contagion because it is the only one of the three effects that exhibits time variation in the 40 weeks of the riots. It is therefore the historical nature of our data that allows us to study diffusion in a dynamic setting, something that most other studies of conflict cannot do.[38]

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

$$\mathbf{riots_t} = \pi + \omega_t \iota + \sum_{s=1}^{L} \beta_s \times \mathbf{W^E} \times \mathbf{riots_{t-s}} + \sum_{r=1}^{L} \lambda_r \mathbf{riots_{t-r}} + \mathbf{u_t} \tag{4}$$

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. The first term π is an $n \times 1$ vector of parish fixed effects that capture all time-invariant parish level factors.[39] 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 all parishes. The term $\sum_{s=1}^{L} \beta_s \times \mathbf{W^E} \times \mathbf{riots_{t-s}}$, where β_s is a parameter, involves time lags of the spatial lag and captures the effect of riots in neighboring parishes at different times in the past. As before, a parish j is considered a neighbor of i if its centroid is within 10kms of i's centroid, and i is not considered to be its own neighbor. 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; they capture the history of riots within each parish. The term $\mathbf{u_t}$ is an $n \times 1$ vector of errors, which include unobserved factors. The assumption needed to isolate the contagion effect is that any correlated and contextual effects are fixed at the parish level througout the duration of the riots or, if they vary, that they can be picked up by the week effects. We estimate

[37] Our identification strategy is robust to them changing, as long as they can be picked up by the week effects.

[38] We emphasize that more recent events (e.g. the London riots in 2011), where riots spread in a matter of days, do not exhibit enough time variation to conduct an analysis of this type, only allowing for a cross-sectional analysis like the one we presented in Section 5.

[39] This means that we cannot control for the observable fundamentals directly. This in part motivated the cross-sectional analysis in Section 5.

equation (4) with an LSDV estimator, correct the standard errors for spatial correlation between parishes with centroids within 10kms of each other (Conley, 1999), and then deploy alternative estimators.[40]

6.1 Baseline results from the panel specification

Table 4 reports estimation results for equation (4). Columns (1) and (2) show specifications with one and three temporal lags, respectively.[41] 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 for up to ten weeks (not shown). 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 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.

The estimates of the first spatial lag $\mathbf{W^E} \times \mathbf{riots_{t-1}}$ in columns (1) and (2) capture the direct impact that an exogenous change in that variable has on $\mathbf{riots_t}$ and can be interpreted as a marginal effect. This is because they enter the panel model with a time lag, ensuring that the feedback process described in Section 5.3 kicks in with a lag. An exogenous increase of one riot in the neighborhood of i in week $t-1$ then leads to an increase in the expected number of riots of about 0.0030 in week t. This direct effect is relatively large, given that the unconditional number of riots in a parish in any given week is 0.005.[42]

[40]The presence of a lagged dependent variable can introduce Nickell bias in fixed effects models. The standard solution, which involves using the GMM estimator 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) shows that the LSDV estimator is the best estimator in situations with more than 30 time periods, as is the case with our data.

[41]Table A8 in the appendix reports specifications with up to ten temporal lags.

[42]The impact of an exogenous riot in a given neighborhood will continue over time. In addition to the direct effect (the coefficient of 0.0030), there are two indirect effects: through the additional time lag of the spatial lag, and through the lagged dependent variable.

The estimate of the coefficient on $\mathbf{W^E} \times \mathbf{riots_{t-1}}$ isolates the contagion effect under the maintained assumption that correlated and contextual effects are picked up by the parish and week effects. This assumption would be violated if some parishes were affected by correlated shocks that varied across time and space. Table 4, columns (3) and (4) report results of augmented versions of equation (4) that control for two types of time shocks. First, to account for economic shocks that might differ across locations based on economic activity, we allow the weekly shocks to be heterogeneous across the four main agricultural areas of England.[43] For a correlated shock not to be captured, it would need to affect only some parishes within an agricultural region. The results are reported in column (3), and we observe that the coefficient on $\mathbf{W^E} \times \mathbf{riots_{t-1}}$ falls from 0.003 to 0.0019, but remains statistically significant at the five percent level. Second, we account for the change in national policy that took place on 23 November 1830. The tougher stance against the riots adopted by the new Whig government could have led to different changes in repression in different counties. To examine this possibility, we augment equation (4) by adding a dummy for the post 23 November 1830 period and in addition interacting it with the county dummies.[44] For this policy shock not to be fully captured, it would need to be the case that the short-term impact differed across parishes within a county. The results are reported in column (4); the point estimate on $\mathbf{W^E} \times \mathbf{riots_{t-1}}$ increases from 0.0029 to 0.0041; the second and third lags are estimated less precisely. Overall, the results reported in columns (3) and (4) suggest that idiosyncratic correlated shocks are not a major concern.

Columns (5) and (6) present two 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. Column (5) reports a specification without these parishes and shows that our results are not driven by the inclusion of Kent. Second, parishes close to London may

[43] We do so by adding the term $\mathbf{Aregion} \times \eta_\mathbf{t}$ to the specification, where **Aregion** is an $n \times 3$ matrix where element (i, j) will equal 1 if parish i is in agricultural region j and 0 otherwise, and $\eta_\mathbf{t}$ is a 3×1 vector of agricultural region-specific coefficients for week t. The omitted agricultural region is "high wage, dairy", which is picked up by the non-interacted week dummies.

[44] We do so by adding $\theta d(t > 23Nov1830)\iota + d(t > 23Nov1830)\mathbf{county} \times \delta$ to the specification, where θ is a scalar coefficient, $d(t > 23Nov1830)$ is a scalar dummy that takes the value of 1 in weeks after the change in government, ι is an $n \times 1$ vector of ones, **county** is an $n \times c$ matrix where entry (i, j) equals 1 if parish i is in county j and 0 otherwise, and δ is a $c \times 1$ vector of coefficients.

Table 4: 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) $\mathbf{riots_t}$	(8) $\mathbf{riots_t}$
$\mathbf{W^E \times riots_{t-1}}$	0.0029	0.0030	0.0019	0.0041	0.0026	0.0030	0.0138	0.0028
	(0.00097)***	(0.00098)***	(0.00090)**	(0.0010)***	(0.0010)**	(0.00099)***	(0.0052)***	(0.0003)***
$\mathbf{W^E \times riots_{t-2}}$		-0.00069	-0.0012	-0.00024	-0.00098	-0.00068	-0.0766	-0.0007
		(0.00035)**	(0.00038)***	(0.00036)	(0.00031)***	(0.00035)*	(0.01386)***	(0.0003)***
$\mathbf{W^E \times riots_{t-3}}$		-0.000090	-0.00041	-0.000011	-0.00028	-0.000054	-0.11621	-0.0005
		(0.00025)	(0.00027)	(0.00027)	(0.00023)	(0.00025)	(0.01919)***	(0.0003)*
$\mathbf{riots_{t-1}}$	0.032	0.031	0.030	0.031	0.025	0.031	-0.331	
	(0.016)**	(0.016)*	(0.016)*	(0.017)*	(0.015)*	(0.017)*	(0.034)***	
$\mathbf{riots_{t-2}}$		-0.016	-0.016	-0.016	-0.018	-0.016	-0.488	
		(0.0065)**	(0.0065)**	(0.0065)**	(0.0070)***	(0.0065)**	(0.0626)***	
$\mathbf{riots_{t-3}}$		-0.021	-0.021	-0.021	-0.022	-0.021	-0.385	
		(0.0054)***	(0.0054)***	(0.0054)***	(0.0057)***	(0.0054)***	(0.071)***	
Observations	403,065	382,395	382,395	382,395	366,670	372,368	382,395	382,395
R-squared	0.002	0.003	0.003	0.004	0.003	0.003	.	.
Fixed effect	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	No	Agricultural region x week	post 23N + county x post 23N	No	No	No	No
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Bootstrap (50)	Spatial
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson	MLE
Note					excl Kent	excl < 20km London		

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Column (7) is estimated using the glmmML package in R. The coefficients in column (7) are Poisson regression coefficients, which can be interpreted as follows: for a one unit increase in the right hand side variable, the regression coefficient captures the difference in the logs of expected counts. Column (8) estimates a maximum likelihood estimator using the splm package in R. The standard errors are adjusted for arbitrary spatial correlation across observations (spatial.error=kkp), using a binary matrix where the 10 closest parishes (by distance) are considered to be neighbors. The coefficient on the first time lag of the spatial lag in column (8) should be compared to 0.0039 (standard error 0.0010), which is obtained by estimating the specification in (8) using OLS and adjusting the errors following Conley (not reported to save on space).

have been different because of their proximity to the capital.[45] Column (6) shows that this was not the case; dropping all parishes within 20kms of London has only a small impact on the results. These checks rule out the possibility that the baseline estimates are unduly influenced by the inclusion of potentially special cases in the sample.

Column (7) and (8) present the results obtained with two alternative estimators. Column (7) reports the estimate from 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, yet the signs and significance levels are consistent with the LSDV results reported in column (2). Column (8) reports the estimates from a maximum likelihood estimator that allows us to adjust the standard errors for arbitrary spatial correlation. The results are comparable to those in the baseline.[46] Taken together, these results show that our estimates of the contagion effect are robust to the choice of estimation technique.

6.2 Reverse causality

The relative short space of time over which the riots spread, together with the observed variation in their timing, has allowed us to isolate the contagion effect by keeping the contextual and correlated effects constant. This, however, does not determine the direction of causality. In particular, 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 $t+2$. The contagion effect we estimated can be seen as a summary of all of these interrelations, which is informative, but in this section we follow two complementary strategies that allow us to make some progress in giving our estimates a causal interpretation.

6.2.1 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

[45]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.

[46]For computational reasons, we cannot include lags of own riots in the estimation. The point estimate on the spatial lags estimated with the LSDV are not sensitive to this restriction, and the LSDV estimation in this case yields a coefficient of 0.0039 on $\mathbf{W^E} \times \mathbf{riots_{t-1}}$.

in this setting. As in Miguel et al. (2004) and many other contributions to the literature on civil war, we define a new $n \times 1$ vector $\mathbf{riotsO_t}$ that measures 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 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 as soon as it experiences a riot. Consequently, it cannot experience the feedback from the impact its riot has on its neighbors.[47]

Table 5 presents estimates of the probability of onset as a function of riots in the neighborhood. We cannot include lags of own riots in these estimations because their value would be constant and equal to 0 throughout. To allow a direct comparison with the previous results, column (1) shows a specification where we estimate incidence without any lags of own riots. Column (2) reports the results from a linear probability model of onset with parish and week fixed effects. We observe that the point estimate on $\mathbf{W^E} \times \mathbf{riots_{t-1}}$ is smaller, as one would expect, than in column (1). This suggests that feedback from parish i back to itself through neighboring parishes may be of some importance. As a robustness check, column (3) reports conditional fixed effect logit estimates. Although the coefficients are not directly comparable (column (3) reports odds ratios), the results are consistent with those in column (2).[48]

6.2.2 Instrumental Variables

Another way to address the possibility of reverse causality is to employ a spatial identification strategy commonly used in the literature on peer effects (e.g., De Giorgi et al., 2010): using the neighbors of the neighbors as an instrumental variable. Specifically, we instrument for riots that happened in week t in the 10km neighborhood of parish i with the total number of riots that took place that same week in parishes that lie between 10 and 20kms away from i.[49] The exclusion restriction is that conditional on parish

[47]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 event.

[48]This is arguably a more appropriate estimator for riot onset. Its downside is that it drops many parishes from the sample because they experienced no riots. An additional complication is that we cannot include week effects because the estimator fails to converge in that case.

[49]See Table A6 in the appendix for summary statistics.

Table 5: The probability of onset of riots

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riotsO_t}$	(3) $\mathbf{riotsO_t}$
$\mathbf{W^E} \times \mathbf{riots_{t-1}}$	0.0039	0.0023	2.3686
	(0.00099)***	(0.00038)***	(0.2012)***
$\mathbf{W^E} \times \mathbf{riots_{t-2}}$	-0.0012	-0.00012	2.1777
	(0.00033)***	(0.00015)	(0.2173)***
$\mathbf{W^E} \times \mathbf{riots_{t-3}}$	-0.00076	0.000040	2.1170
	(0.00026)***	(0.000096)	(0.2155)***
Observations	382,395	363,475	20,742
R-squared	0.002	0.002	.
Parish FE	Yes	Yes	Yes
Week FE	Yes	Yes	No
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. $\mathbf{riotsO_t}$ measures 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 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 as soon as it experiences a riot. Column (3) reports the odds ratios. There is a significant drop in observations in column (3) relative to column (2) because parishes that experience no riots are dropped by the estimator.

and week fixed effects, riots 10-20kms away from parish i only have an effect on its riots through the impact they have on riots in i's more immediate neighborhood (within 10kms). This is plausible because the prevailing communication technologies of the time forced information about the riots to spread in a spatially continuous way.

Table 6, columns (1) and (2) present the 2SLS estimates, with one and three spatial lags, respectively. The signs and significance of the coefficients on the spatial lags remain unchanged except for the fact that the riots in the neighborhood at $t-3$ are no longer significant. The coefficients on the temporal lags of own riots are smaller and less precisely estimated, but the overall pattern of the signs is the same as it was before. The coefficients on the spatial lags are roughly three times larger than those in table 4, and an exogenous riot in the neighborhood of a parish leads to an increase of about 0.009 riots. In short, the effect of a riot nearby is to nearly triple the incidence of riots relative to the counterfactual of no riots nearby.

We have previously shown that there is a fair amount of heterogeneity in how the riots spread, and that this heterogeneity is partly captured by the fundamentals. 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 riots 10-20 kilometers away triggered riots in parishes within their 10 kilometer radius. This subset of parishes may be more prone to riots than the average parish; if that is the case, then it would explain why the IV estimates are about three times the size of those obtained with the LSDV estimator.

7 The mechanisms: Local and national information flows

We now explore two specific mechanisms that might explain the diffusion of the Swing riots. They concern information transmission at the local and national level.

7.1 Diffusion: Does local information matter?

The Swing riots could have diffused when potential rioters in one parish learned about riots in neighboring parishes, their law enforcement consequences, or the local concessions granted to the participants. To explore this possibility we study the effect that fairs had on riots in surrounding parishes. Fairs could have served as local information hubs where the traders, farmers and farm laborers from the region, who had congregated to trade, also exchanged local information about recent events.

The location and dates of fairs are reported in Owen (1827). Although the location of a fair could be related to a number of factors that were also relevant to the riots, the *timing* of fairs was probably not. These dates and locations were set far in advance to coincide with events in the agricultural calendar.[50] This allows us to exploit the fact

[50] 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.

Table 6: Instrumental variables estimation

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W^E} \times \mathbf{riots_{t-1}}$	0.0088	0.0089
	(0.0011)***	(0.0014)***
$\mathbf{W^E} \times \mathbf{riots_{t-2}}$		-0.0027
		(0.00056)***
$\mathbf{W^E} \times \mathbf{riots_{t-3}}$		0.00048
		(0.00033)
$\mathbf{riots_{t-1}}$		0.014
		(0.018)
$\mathbf{riots_{t-2}}$		-0.012
		(0.0066)*
$\mathbf{riots_{t-3}}$		-0.022
		(0.0042)***
Observations	403,065	382,395
Number of parishes	10,335	10,335
Parish FE	YES	YES
Week FE	YES	YES
Standard errors	Clustered	Clustered
Estimation	2SLS	2SLS
Instrumented	$\mathbf{W^E} \times \mathbf{riots_{t-1}}$	$\mathbf{W^E} \times \mathbf{riots_{t-1}}$ $\mathbf{W^E} \times \mathbf{riots_{t-2}}$ $\mathbf{W^E} \times \mathbf{riots_{t-3}}$
Instrument	Riots 10-20kms (t-1)	Riots 10-20kms (t-1)
F-test excluded instruments	1564.90	509.61
SW underid (p-value)	1565.20	1318.93
SW weak id (p-value)	1564.9	1318.66
Instrument		Riots 10-20kms (t-2)
F-test excluded instruments		849.12
SW underid (p-value)		2491.18
SW weak id (p-value)		2490.67
Instrument		Riots 10-20kms (t-3)
F-test excluded instruments		826.02
SW underid (p-value)		2431.08
SW weak id (p-value)		2430.58
KP Wald rk F	1564.90	246.26

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The instrument for riots that took placed within a 10km radius of a parish are the riots that took place that same week in parishes between 10 and 20kms away. The null hypothesis in the SW underid test is that the endogenous regressor is unidentified. The null hypothesis in the SW weak id test is that the instrument is weak. The KP Wald rk test is a weak instrument test that is robust to non-iid errors.

that the timing of the fairs was plausibly exogenous to the riots.[51] To do so we augment equation (4) by adding the following terms

$$\gamma \mathbf{fairsN_{t-1}} + \phi \mathbf{riotsN_{t-1}} \times \mathbf{fairsN_{t-1}}, \tag{5}$$

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

Table 7 reports the results. Column (1) shows the 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, and 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. This is consistent with the hypothesis that fairs served as local information

[51] 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 i's neighbors. This restriction requires an assumption on the extent of the region served by the fair. Furthermore, it reduces the sample to only those parishes that are far enough (but not too far) from a fair, and this changes every week as the location of the fairs changes, meaning that the sample changes from week to week.

Table 7: Diffusion and the timing of fairs

VARIABLES	(1) $\mathbf{riots_t}$	(2) $\mathbf{riots_t}$
$\mathbf{W^E} \times \mathbf{riots_{t-1}}$	0.0029	0.0025
	(0.00097)***	(0.00094)***
$\mathbf{riots_{t-1}}$	0.032	0.033
	(0.016)**	(0.016)**
$\mathbf{fairsN_{t-1}}$	0.0028	0.00090
	(0.00090)***	(0.00075)
$\mathbf{riotsN_{t-1}} \times \mathbf{fairsN_{t-1}}$		0.036
		(0.0091)***
Observations	403,065	403,065
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. $\mathbf{fairsN_{t-1}}$ is an $n \times 1$ vector where element i equals 1 if at least one fair occurred within 10kms of the parish i's centroid at time $t-1$ and 0 otherwise. $\mathbf{riotsN_{t-1}} \times \mathbf{fairsN_{t-1}}$ is an $n \times 1$ vector where entry i equals 1 if there was at least one riot within 10kms of i's centroid *and* at least one fair within 10kms of i's centroid. We ran the specification in columns (1) and (2) but with three time lags and interactions (not reported), and the results are consistent with what is reported here.

hubs.[52] To get a sense for the size of the effect estimated in column (2), consider a parish i that has experienced no riots and has seen no riots in its vicinity. If at $t-1$ there is a riot in its neighborhood, in the absence of a fair at $t-1$ it will expect the number of riots it experiences at time t to increase by 0.0025, but if the neighboring riot coincides with a neighboring fair at time $t-1$, the impact of this nearby riot more than doubles to $0.0025 + 0.0036 = 0.0061$.[53] Fairs have a substantial impact on the magnitude of contagion.[54]

[52]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 this coordination and organization role was the only reason fairs mattered.

[53]We ran the specification in columns (1) and (2) with three time lags and interactions (not reported), and the results are consistent with what is reported in the table.

[54]As discussed before, the total effect will in fact be greater, since over time there will feedback between neighboring parishes.

7.2 Diffusion: Does national information matter?

We have found strong evidence that information travels locally, either between neighboring parishes or through fairs, and that this has a considerable impact on contagion. However, it is also possible that national information flows helped drive contagion. Such flows could have acted as a complement to local information, or it could be that the local effect that we find is an artifice of the way in which national information flowed. National information about the riots and about repression efforts by the authorities spread through the newspapers, which reported extensively on the riots, and along the coach network. These ways of accessing information would have been open to a type of individual different from the average Swing rioter: newspapers had to be read and a large fraction of the rural population was illiterate; coach travel was expensive, and so travelers were generally wealthier than the average population. If national news reached the farm laborers and affected their involvement in the riots, it is likely that it was through the intervention of village radicals.[55] The national news about riots in other parts of the country may have led these radicals to organize collective action in their villages.

We examine the role of national information in the diffusion process by studying two variables that measure whether parishes were closely connected to the national news grid: closeness to a local newspaper and closeness to a coach stop. First, we introduce an $n \times 1$ vector **newspaperN** where element i equals 1 if parish i was close (its centroid was within 10kms) of where a local or regional newspaper was printed.[56] At the time, local and regional newspapers mostly reprinted material that had previously been published in the London newspapers, and so we can think of them as spreading national news (Barker, 2000). Second, we introduce an $n \times 1$ vector **coachstopN** where element i equals 1 if parish i was close (its centroid was within 1km) of a coach stop.[57] In the early 1830s the coach network radiated out from London and connected the rest of the country to the capital. Coaches traveled along the existing turnpike roads, making stops at pre-established locations, and being close to a coach stop would have improved a parish's

[55]In Section 5 we presented some evidence suggesting that village radicals served as coordinators of the riots.

[56]These data come from House of Commons (1833); more details can be found in the online appendix.

[57]These data come from Bates (1969); more details can be found in the online appendix.

access to national information originating in the London news market.[58] 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 (4) with interaction terms between **newspaperN** and **coachstopN** respectively and an $n \times n$ diagonal matrix $\mathbf{riotsN_{t-1}}$ where entry (i, i) equals 1 if there was at least one riot in a parish within 10kms of i's centroid (but excluding riots in i itself) at time $t-1$, 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.

Table 8, 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 at $t-1$ there is one riot in its neighborhood, its expected number of riots at time t increases by 0.0025 if it is not close to a newspaper; if it is near a newspaper, the expected increase in riots will be more than 50 percent larger, $0.0025 + 0.0018 = 0.0043$. Column (2) reports the effect of the proximity to coach stops, and again we find that parishes located near coach stops experience a much stronger contagion effect, again about 50 percent larger. Together these results show that nearby riots have a larger impact on connected parishes, which is consistent with national news feeding 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 south-east 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 closeness to newspapers and coach stops could be capturing heterogeneity induced by some other factors.

[58] We use 1km because individuals would have needed to be close to the coach stop to hear information first-hand from travelers; otherwise information would have had to spread from the coach stop through the local network of contacts, but that would be a test of the joint hypothesis that national and local information mattered for the spread of the riots.

Table 8: National information: 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) $\mathbf{riots_t}$
$\mathbf{W^E} \times \mathbf{riots_{t-1}}$	0.0025	0.0028	0.0029	0.0029	0.0029	0.0029
	(0.00095)***	(0.00097)***	(0.00097)***	(0.00097)***	(0.00097)***	(0.00097)***
$\mathbf{riots_{t-1}}$	0.033	0.032	0.032	0.032	0.032	0.032
	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**	(0.016)**
$\mathbf{riotsN_{t-1}} \times \mathbf{newspaperN}$	0.018					
	(0.0056)***					
$\mathbf{riotsN_{t-1}} \times \mathbf{coachstopN}$		0.014				
		(0.0066)**				
$\mathbf{newspaperN} \times d\,(t > 25Oct1830)$			-0.00052			
			(0.00098)			
$\mathbf{coachstopN} \times d\,(t > 25Oct1830)$				0.0047		
				(0.0016)***		
$\mathbf{newspaperN} \times d\,(t > 23Nov1830)$					-0.0016	
					(0.0011)	
$\mathbf{coachstopN} \times d\,(t > 23Nov1830)$						-0.00083
						(0.0018)
Observations	403,065	403,065	403,065	403,065	403,065	403,065
R-squared	0.003	0.002	0.002	0.002	0.002	0.002
Parish FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	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. $\mathbf{riotsN_{t-1}}$ is an $n \times n$ diagonal matrix where entry (i, i) equals 1 if there was at least one riot in a parish within 10kms of i's centroid (but excluding riots in i itself) and 0 otherwise. **newspaperN** and **coachstopsN** are $n \times 1$ vectors with element i set to 1 if there was a newspaper or coach stop in the vicinity 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.

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 steep increase in the number of riots at the end of October 1830. At this point the uprising stopped being a local issue in Kent and assumed national significance with numerous reports in the national press. We conjecture that the acceleration of the uprising was due disproportionally to connected parishes; this could be, for example, if village radicals were induced to organize riots after reading about the events in Kent in a local newspaper or hearing about them at the inns and pubs along the coach network. The second event is the change in government on November 23 1830. As discussed previously, the new Whig administration took a tougher stance than the previous Tory government and encouraged repression. News about the change in government and the new policy on repression may have made some village radicals less willing to organize or support local riots.

To test this hypothesis we augment equation (4) with interactions between **newspaperN** and **coachstopN** respectively and a scalar dummy variable $d\,(t > 25Oct1830)$ that equals 1 for periods 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 8, columns (3) and (4) present the results for newspapers while columns (5) and (6) present the results for the coach network. We find that connected parishes played a larger role in the acceleration of the protest than unconnected ones, although the effect is only statistically significant for parishes located close to coach stops.[59] 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 are negative as expected but not statistically significant. These results offer some mixed evidence for the hypothesis that national information, transmitted by local and regional newspapers and along the coach network, facilitated diffusion.[60]

[59]The weeks after 25th October saw a large increase in the number of riots. Our regressions show the extent to which this was due to a disproportionate increase in riots in areas near newspapers and coach stops.

[60]In evaluating these results, it is important to bear in mind that we cannot rule out that they are due to unobserved parish heterogeneity proxied by the presence of newspapers and coach stops. The

8 Conclusions

In this paper we use data from a specific episode of collective violence, the Swing riots of 1830-1831, to address two related questions. First, we examine the causes of the riots, with a particular focus on the importance of economic and social fundamentals relative to contagion. Second, we investigate the specific mechanisms that may have driven the diffusion of these riots, focusing on the importance of local and national sources of information. The Swing riots provide an ideal setting in which to address these questions: they were historically important in that they contributed to the reform of the rules governing elections (Aidt and Franck, 2015), they allow us to assign fundamentals to each specific riot event, and the relatively slow speed of their spread enable 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 6 by contagion. This contagion is mostly due to local flows of information between neighboring parishes or participants at local fairs. The evidence for the role of national information in driving contagion is mixed.

Are the lessons from the Swing riots still be 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) have played a key role in recent 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.[61] This work suggests that although the technology has changed, causing the diffusion process to speed up, the underlying social interactions behind this process 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

connected parishes may simply have been different from the rest in ways that influenced how vulnerable they were to contagion.

[61] 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.

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. The Swing riots provide us with valuable lessons that can help inform our response to the most recent incarnation of these challenges.

References

Acemoglu, D., S. Naidu, P. Restrepo, and J. A. Robinson (2014). Democracy does cause growth. Working Paper 20004, National Bureau of Economic Research.

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

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

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

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

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

Anselin, L. (1998). *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic.

Archer, J. E. (2000). *Social Unrest and popular protest in England, 1780-1840.* Cambridge, England: Cambridge University Press.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies 58*(2), 277–297.

Barbera, S. and M. O. Jackson (2016). A model of protest, revolution and information, Unpublished workingpaper.

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

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

Baudains, P., A. Braithwaite, and S. Johnson (2013). Target choice during extreme events: A discrete spatial choice model of the 2011 London riots. *Criminology 51*(2), 251–285.

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

Blume, L. E., W. A. Brock, S. N. Durlauf, and Y. M. Ioannides (2011). Identification of social interactions. In A. B. Jess Benhabib and M. O. Jackson (Eds.), *Handbook of Social Economics*. Amsterdam: North-Holland.

Bohstedt, J. (2010). *The politics of provisions food riots, moral economy, and market transition in England, c. 1550-1850.* Farnham: Ashgate.

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

Bramoullè, Y., H. Djebbari, and B. Fortin (2009). Identification of peer effects through social networks. *Journal of Econometrics 150*(1), 41 – 55.

Brock, W. A. and S. N. Durlauf (2001). Discrete choice with social interactions. *The Review of Economic Studies 68*(2), 235–260.

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

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

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

Cannon, J. A. (1973). *Parliamentary reform, 1640-1832.* Cambridge, UK: Cambridge University Press.

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

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

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

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

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

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

Crabtree, C., D. Darmofal, and H. L. Kern (2015). A spatial analysis of the impact of West German television on protest mobilization during the East German revolution. *Journal of Peace Research 52*(3), 269–284.

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

De Giorgi, G., M. Pellizzari, and S. Redaelli (2010, April). Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics 2*(2), 241.

Dell, M. (2015). Trafficking networks and the mexican drug war. *American Economic Review 105*(6), 1738–1779.

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

Do, Q.-A. and F. Campante (2009). Keeping dictators honest: The role of population, Unpublished workingpaper.

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

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from Colombia. *The Review of Economic Studies 80*(4), 1384–1421.

Dyck, I. (1992). *William Cobbett and rural popular culture*. Cambridge UK: Cambridge University Press.

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

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

Esteban, J. and D. Ray (1999). Conflict and distribution. *Journal of Economic Theory 87*(2), 379–415.

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

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

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

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

Halévy, E. (1923). *Histoire du peuple anglais au XIXe siécle, Vol. 3, De la crise du Reform Bill á l'avénement de Sir Robert Peel (1830-1841).* Paris: Librairie Hachette.

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

Harari, M. and E. La Ferrara (2014). Conflict, climate and cells: A disaggregated analysis. *IGIER working paper* (461).

Harrison, L. F. C. (1989). *The Common People, a History from the Norman Conquest to the Present.* Glasgow, UK: Fontana.

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

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

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

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

House of Commons (1833). Newspaper stamps, england. return to an order of the honourable house of commons, dated 24 may 1833; for, an account of the number of stamps issued to each of the provincial newspapers in england, in the year ending on 1st april 1833. *Parliamentary Papers, Accounts and Papers 569.*

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

Jia, R. (2014). Weather shocks, sweet potatoes and peasant revolts in historical China. *The Economic Journal 124*(575), 92–118.

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

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

Judson, R. A. and A. L. Owen (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters 65*(1), 9 – 15.

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

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

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

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

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

Lohmann, S. (1994, 10). The dynamics of informational cascades: The monday demonstrations in Leipzig, East Germany 1989-91. *World Politics 47*, 42–101.

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

Maehl, W. H. (1967). Introduction. In W. H. Maehl (Ed.), *The reform bill of 1832*, pp. 1–8. New York, Holt, Rinehart and Winston.

Manski, C. (1993). Identification of endogenous social effects the reflection problem. *Review of Economic Studies 60*(3), 531–542.

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

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

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

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

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

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

Royle, E. (2000). *Revolutionary Britannia? Reflection on the Threat of Revoution in Britain, 1789-1848.* Manchester, UK: Manchester University Press.

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

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

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

Shaw-Taylor, L. (2001). Parliamentary enclosure and the emergence of an english agricultural proletariat. *Journal of Economic History 61*(3), 640–662.

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

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

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

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

Tullock, G. (1971). The paradox of revolution. *Public Choice 11*, pp. 89–99.

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

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

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

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

A Data Appendix (not for publication)

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

The following variables have 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).

- $\mathbf{W^E} \times \mathbf{riots_t}$ is an an $n \times 1$ vector where element i corresponds to the total number of riots that took place in week t 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).

- $\mathbf{fairsN_t}$ 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 10kms of its own centroid. The information on fairs comes from Owen (1827), which contains a directory of fairs in England and Wales in 1827. The GIS used to georeference the fairs are 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 the total number of riots that took place in a parish between June 28 1830 and April 3 1831. Source: Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- *Riots neighborhood (10km)* is the total number of riots that took place in the neighborhood of a parish (where the neighborhood of parish i is made up of all parishes with centroids within a 10km radius of parish i's). Parish i is not considered to be its own neighbor. Source: constructed from Hobsbawm and Rudé (1973, Appendix II) and Holland (2005). Geo-referenced using Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- *Log population 1831* is the natural logarithm of the total number of inhabitants in a parish in 1831 (in 1000s). Source: Census of Great Britain, 1831. Wrigley, Shaw-Taylor and Newton (2010).

- *Log Urbanization* is the number of inhabited and uninhabited houses and buildings in a parish per English statute acre. Source: Census of Great Britain, 1831, Wrigley, Shaw-Taylor and Newton (2010), for data on houses and buildings; the area is calculated from Satchell, Kitson, Newton, Shaw-Taylor, and Wrigley (2016).

- *Share of families in agriculture* is the number of families chiefly employed in agriculture as a percentage of the total number of families in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Low wage, cereal* is a region dummy variable equal to one for parishes in the low wage cereal growing regions of England, i.e. in the south-east and East Anglia. Source: Caird (1852).

- *High wage, cereal* is a region dummy variable equal to one for parishes in the high wage cereal growing regions of England, i.e. northeast of England. Source: Caird (1852).

- *Low wage, dairy* is a region dummy variable equal to one for parishes in the low wage dairy farming regions of England, i.e. in Cornwall, the southwest of England, parts of Wales and the Midlands. Source: Caird (1852).

- *Emp. share of agricultural workers* is the number of male laborers aged 20 or over employed in agriculture as a percentage of all males aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Emp. share of farmers/landowners* is the number of male agricultural occupiers (tenant farmers or landowners) aged 20 or over as a percentage of all males aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Emp. share in manufacturing* is the number of males aged 20 or over employed in manufacturing or in making manufacturing machinery as a percentage of all males aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Emp. share in trade and handicraft* is the number of males aged 20 or over employed in trade or in handicraft as masters or workmen as a percentage of all males aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Emp. share of professionals* is the number of males aged 20 or over classified as capitalists, bankers, professionals and other educated men as a percentage of all males aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Farm labor – farmer ratio* is the ratio of agricultural workers aged 20 or over to the number of male tenant farmers and landowners aged 20 or over in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Male share* is the number of males aged 20 or over as a percentage of the total population in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Enclosed before 1831* is a binary variable that equals 1 if the parish was affected by any enclosure acts dated 1830 or earlier, and 0 otherwise. Source: Tate (1978); Satchell, Boothman, Shaw-Taylor, and Bogart (2016).

- *Inequality* is the annual value of real property in a parish (as assessed in April 1815) per capita (according to the 1821 census). 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).

- *Log middle class* is the natural logarithm of the number of males aged 20 or over employed as masters or workmen in trade and handicraft in a parish. Source: Census of Great Britain, 1831; Wrigley, Shaw-Taylor and Newton (2010).

- *Near market* is a dummy variable equal to one for parishes located within a 1km 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. The GIS used to georeference the markets are Shaw-Taylor, Satchell, and Newton (2016) and Satchel, Shaw-Taylor, and Potter, (2016).

- *Near coach stop* is a dummy variable equal to one for parishes located within 1km of a coach stop on the stage coach route. 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.

- *Petitions 1828-31* is the number of petitions originating from each parish and submitted to the House of Commons between 1828 and 1831. Most of the petitions 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).

- *Log distance to garrison* 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).

- *Near police force* is a dummy variable equal to one if a parish is located within a 1km radius of a town with a police force. Source: Clark (2014).

- **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 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. 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.

- **coachstopN** is an $n \times 1$ vector where element i is equal to one if parish i was within 1km 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. Satchell, Newton, Bogart, and Shaw-Taylor (2014).

B Appendix: Additional cross-sectional results (not for publication)

This section presents some additional cross-sectional results. Table A1 shows the summary statistics for the riot variables and the fundamentals.

A1: Cross-section: summary stats

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Riots	10,335	0.22	0.91	0	20
Riots neighborhood (10km)	10,335	6.48	9.51	0	102
Riots neighborhood (10-20km)	10,335	18.2	22.0	0	169
Log Urbanization	9,702	2.55	1.44	0	9.73
Log population 1831	10,317	6.11	1.24	0	12.0
Share of families in agriculture	10,284	59.7	26.9	0	100
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
Emp. share of agricultural workers	10,281	47.1	22.3	0	100
Emp. share of farmers/landowner	10,281	13.4	10.4	0	100
Emp. share in manufacturing	10,281	1.97	7.61	0	85.7
Emp. share in trade and handicraft	10,281	19.9	13.8	0	100
Emp. share of professionals	10,281	3.33	5.75	0	99.1
Farm labour - farmer ratio	10,317	5.14	5.05	0	119
Male share	10,317	25.5	3.94	0	80
Enclosed before 1831	10,335	0.36	0.48	0	1
Inequality (tax / 1821 population)	9,492	7.73	8.87	0	318
Log middle class	10,317	3.02	1.58	0	9.86
Near market (1 km)	10,335	0.067	0.25	0	1
Near coach stop (1 km)	10,335	0.051	0.22	0	1
Petitions 1828-31	10,335	0.57	1.85	0	57
Near newspapers	10,335	0.014	0.19	0	5
Log distance to garrison	10,335	10.7	0.88	3.51	11.9
Near police force (1km)	10,335	0.026	0.16	0	1

Table A2 considers the impact these fundamentals have on the incidence of riots by estimating the following specification

$$riots_i = \alpha + \gamma' \times \mathbf{fundamentals}_i + u_i$$

where $riots_i$ is the total number of riots in parish i, α is a constant, the vector $\mathbf{fundamentals}_i$ has length k which equals the number of fundamentals and lists the fundamentals for parish i, while γ is a vector of length k.

A2: Cross-section of fundamentals

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots	(7) Riots (bin)	(8) Riots
Log Urbanization	-0.053	-0.070	-0.065	-0.087	-0.081	-0.070	-0.031	-0.31
	(0.015)***	(0.015)***	(0.016)***	(0.020)***	(0.018)***	(0.017)***	(0.0061)***	(0.070)***
Log population 1831	0.16	0.16	0.17	0.11	0.12	0.12	0.042	0.44
	(0.020)***	(0.021)***	(0.028)***	(0.032)***	(0.032)***	(0.033)***	(0.012)***	(0.19)**
Share of families in agriculture	0.00041	0.0021	0.0024	0.0024	0.0024	0.0020	0.00057	0.0086
	(0.00065)	(0.0010)**	(0.0011)**	(0.0011)**	(0.0011)**	(0.00098)**	(0.00035)	(0.0054)
High wage, cereal	0.029	0.019	0.022	0.017	0.032	0.077	0.018	0.12
	(0.026)	(0.026)	(0.028)	(0.028)	(0.030)	(0.040)*	(0.016)	(0.39)
Low wage, dairy	0.063	0.062	0.070	0.074	0.070	-0.064	-0.011	-0.53
	(0.026)**	(0.025)**	(0.027)***	(0.027)***	(0.027)**	(0.069)	(0.017)	(0.59)
Low wage, cereal	0.37	0.36	0.37	0.37	0.39	0.43	0.13	0.64
	(0.045)***	(0.046)***	(0.050)***	(0.050)***	(0.055)***	(0.17)***	(0.039)***	(0.60)
Emp. share of agricultural workers		-0.00063	-0.00070	-0.00048	-0.00051	-0.00035	-0.00017	0.0037
		(0.00095)	(0.0011)	(0.0011)	(0.0011)	(0.00099)	(0.00041)	(0.0059)
Emp. share of farmers/landowner		-0.00086	-0.00019	-0.00029	-0.00032	0.0014	0.00033	-0.0055
		(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.00050)	(0.0087)
Emp. share in manufacturing		-0.00049	-0.00067	-0.00095	-0.0014	-0.00072	0.00098	0.0066
		(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.00054)*	(0.0066)
Emp. share in trade and handicraft		0.0038	0.0043	0.00024	0.00014	0.00084	0.00027	0.0054
		(0.0011)***	(0.0011)***	(0.0017)	(0.0017)	(0.0018)	(0.00070)	(0.0093)
Emp. share of professionals		0.0038	0.0037	0.0025	0.0032	0.0053	0.0018	0.019
		(0.0018)**	(0.0022)*	(0.0024)	(0.0024)	(0.0026)**	(0.00070)***	(0.019)
Farm labour - farmer ratio			0.0042	0.0037	0.0036	-0.00012	0.00068	-0.0051
			(0.0028)	(0.0028)	(0.0028)	(0.0027)	(0.00096)	(0.0064)
Male share			-0.0077	-0.0096	-0.0094	-0.0094	-0.0032	-0.082
			(0.0020)***	(0.0021)***	(0.0021)***	(0.0024)***	(0.00086)***	(0.019)***
Enclosed before 1831			0.029	0.028	0.022	0.011	0.013	0.16
			(0.030)	(0.030)	(0.029)	(0.023)	(0.0074)*	(0.095)*
Inequality (tax / 1821 population)			0.0033	0.0027	0.0028	0.0023	0.00060	-0.0017
			(0.0015)**	(0.0013)**	(0.0013)**	(0.0011)**	(0.00032)*	(0.011)
Log middle class				0.066	0.065	0.061	0.022	0.35
				(0.026)**	(0.025)**	(0.026)**	(0.011)**	(0.18)*
Near market (1 km)				0.23	0.23	0.23	0.080	0.23
				(0.085)***	(0.087)***	(0.083)***	(0.027)***	(0.16)
Near coach stop (1 km)				0.091	0.083	0.059	0.030	-0.042
				(0.083)	(0.089)	(0.082)	(0.029)	(0.17)
Petitions 1828-31				0.0085	0.0088	0.0098	0.0032	-0.0042
				(0.0080)	(0.0080)	(0.0081)	(0.0028)	(0.016)
Near newspapers				-0.016	-0.018	-0.010	0.036	-0.0039
				(0.056)	(0.055)	(0.050)	(0.022)	(0.11)
Log distance to garrison					0.026	0.016	0.0022	0.13
					(0.021)	(0.026)	(0.0076)	(0.080)
Near police force (1km)					-0.031	-0.13	-0.046	0.12
					(0.095)	(0.100)	(0.036)	(0.28)
const	-0.84	-0.92	-0.92	-0.58	-0.90	-1.03	-0.27	-6.19
	(0.15)***	(0.17)***	(0.25)***	(0.24)**	(0.32)***	(0.42)**	(0.12)**	(1.59)***
Observations	9,669	9,665	9,266	9,266	9,266	9,266	9,266	9,266
R-squared	0.111	0.112	0.116	0.119	0.119	0.167	0.230	
Dummies	No	No	No	No	No	County	County	County
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Cluster by par
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Columns 1 through 5 add the fundamentals incrementally. Column 6 includes county fixed effects. Column 7 uses a binary version of the left hand side variable which equals

1 if there were any riots in that parish, and 0 otherwise. Column 8 runs a Poisson specification.

In Table A3 we consider the impact of adding spatial lags: one that counts the total number of riots in a 10km radius from the centroid of the parish. The specification we run is:

$$riots_i = \alpha + \beta_1 riots_{i,<10km} + \gamma' \times \mathbf{fundamentals}_i + u_i$$

where $riots_i$ is the total number of riots in parish i, $riots_{i,<10km}$ is the total number of riots in parishes with centroids within 10 kms of parish i's centroid (but excluding parish i itself), and the vector $\mathbf{fundamentals}_i$ lists a number of characteristics for parish i. This specification is a standard spatial autoregressive model where the spatial lag captures the endogenous effect. This specification involves a specific weighting matrix that gives all riots within the neighborhood the same weight of 1, 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).

A3: Diffusion

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots(bin)	(7) Riots
Riots neighborhood (10km)	0.021	0.022	0.018	0.020		0.0051	0.023
	(0.0044)***	(0.0035)***	(0.0037)***	(0.0034)***		(0.00082)***	(0.0035)***
Riots neighborhood (10-20km)			0.0047	0.0065		0.00096	0.0041
			(0.0017)***	(0.0015)***		(0.00043)**	(0.0019)**
Log Riots neighborhood (10km)					0.13		
					(0.022)***		
Log Riots neighborhood (10-20km)					0.044		
					(0.014)***		
Log Urbanization		-0.084	-0.080	-0.083	-0.084	-0.034	-0.37
		(0.017)***	(0.016)***	(0.014)***	(0.016)***	(0.0058)***	(0.070)***
Log population 1831		0.14	0.14	0.15	0.14	0.048	0.46
		(0.034)***	(0.033)***	(0.032)***	(0.033)***	(0.012)***	(0.20)**
Share of families in agriculture		0.0016	0.0014	0.0014	0.0017	0.00041	0.0061
		(0.00089)*	(0.00093)	(0.00095)	(0.00095)*	(0.00034)	(0.0051)
High wage, cereal		0.067	0.068	0.057	0.089	0.016	-0.045
		(0.028)**	(0.031)**	(0.024)**	(0.035)**	(0.014)	(0.39)
Low wage, dairy		-0.026	-0.019	0.024	-0.016	0.00016	-0.32
		(0.057)	(0.061)	(0.020)	(0.061)	(0.016)	(0.64)
Low wage, cereal		0.24	0.19	0.049	0.35	0.070	0.22
		(0.11)**	(0.11)*	(0.031)	(0.15)**	(0.030)**	(0.65)
Emp. share of agricultural workers		-0.00037	-0.00030	-0.00025	-0.00053	-0.00016	0.0025
		(0.00098)	(0.00099)	(0.0010)	(0.00099)	(0.00040)	(0.0056)
Emp. share of farmers/landowner		0.0019	0.0022	0.0022	0.0019	0.00051	-0.00088
		(0.0012)	(0.0012)*	(0.0012)*	(0.0012)	(0.00050)	(0.0084)
Emp. share in manufacturing		-0.0011	-0.0013	-0.0016	-0.0019	0.00083	0.0088
		(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.00054)	(0.0063)
Emp. share in trade and handicraft		0.0015	0.0015	0.0015	0.0015	0.00044	0.0054
		(0.0019)	(0.0018)	(0.0018)	(0.0018)	(0.00070)	(0.0096)
Emp. share of professionals		0.0059	0.0060	0.0054	0.0055	0.0020	0.019
		(0.0027)**	(0.0027)**	(0.0026)**	(0.0026)**	(0.00071)***	(0.018)
Farm labour - farmer ratio		0.000074	6.4e-06	0.00065	-0.00021	0.00072	-0.0019
		(0.0024)	(0.0024)	(0.0023)	(0.0026)	(0.00091)	(0.0063)
Male share		-0.0087	-0.0087	-0.0082	-0.0085	-0.0030	-0.083
		(0.0024)***	(0.0024)***	(0.0022)***	(0.0024)***	(0.00083)***	(0.019)***
Enclosed before 1831		-0.00033	0.00022	-0.0054	-0.00028	0.011	0.12
		(0.021)	(0.021)	(0.021)	(0.022)	(0.0072)	(0.093)
Inequality (tax / 1821 population)		0.0032	0.0035	0.0037	0.0026	0.00091	0.0062
		(0.0011)***	(0.0012)***	(0.0013)***	(0.0011)**	(0.00035)***	(0.0077)
Log middle class		0.050	0.048	0.046	0.049	0.019	0.34
		(0.026)*	(0.026)*	(0.025)*	(0.026)*	(0.010)*	(0.18)*
Near market (1 km)		0.24	0.23	0.23	0.24	0.081	0.26
		(0.080)***	(0.080)***	(0.081)***	(0.081)***	(0.026)***	(0.17)
Near coach stop (1 km)		0.073	0.071	0.072	0.065	0.033	-0.0024
		(0.083)	(0.083)	(0.086)	(0.083)	(0.030)	(0.16)
Petitions 1828-31		0.011	0.011	0.0096	0.011	0.0035	-0.0041
		(0.0082)	(0.0081)	(0.0078)	(0.0082)	(0.0028)	(0.016)
Near newspapers		-0.011	-0.014	-0.013	-0.019	0.035	-0.011
		(0.050)	(0.050)	(0.050)	(0.050)	(0.022)	(0.11)
Log distance to garrison		0.015	0.014	0.038	0.025	0.0018	0.017
		(0.015)	(0.017)	(0.011)***	(0.023)	(0.0059)	(0.078)
Near police force (1km)		-0.19	-0.19	-0.17	-0.15	-0.060	0.15
		(0.10)*	(0.10)*	(0.098)*	(0.099)	(0.037)	(0.28)
const	0.029	-1.09	-1.08	-1.26	-1.44	-0.28	-4.63
	(0.031)	(0.28)***	(0.30)***	(0.27)***	(0.42)***	(0.099)***	(1.59)***
Observations	10,335	9,266	9,266	9,266	9,266	9,266	9,266
R-squared	0.139	0.191	0.195	0.189	0.178	0.245	
Dummies	County	County	County	NO	County	County	County
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Cluster by par
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

We now introduce a set of variables that account for the contextual effects, resulting in a specification that is equivalent to a spatial Durbin model, which in matrix notation is of the form

$$\mathbf{riots} = \alpha\mathbf{I} + \beta_1 \mathbf{riots_{<10km}} + \mathbf{fundamentals} \times \gamma + \mathbf{W} \times \mathbf{fundamentals} \times \rho + \mathbf{Icounty} + \mathbf{u}$$

where **riots** and $\mathbf{riots_{<10km}}$ are vectors, **fundamentals** is an $n \times k$ matrix where n is the number of parishes and k is the number of fundamentals, with row i corresponding to the fundamentals for parish i, $\mathbf{W}$ is an $n \times n$ row normalized weight matrix (so that the sum of entries in any row j adds to 1), so that the entries corresponding to parishes within 10kms of each other are non-zero, while all other entries are set to zero. Furthermore, the fact that the matrix is row-normalized implies that it averages the fundamentals across neighboring parishes. **Icounty** is a $n \times c$ matrix where element (i, j) equals 1 if parish i is in county j and zero otherwise, and $\mathbf{u}$ is a vector of errors. The parameters α and β_1 are real numbers, while γ and ρ are vectors of length n.

The results are reported in table A4. Each column corresponds to the same column in table A3, with the addition of the contextual effects (to keep the tables manageable the coefficients on own fundamentals are not reported). There are two main takeaways from this table: first, the coefficients on the spatial lags are only minimally affected, and second, the contextual effects are largely zero. The main message to come out of this table is that contextual effects appear to be largely absent.

A4: Diffusion and Contextual Effects

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots(bin)	(7) Riots
Riots neighborhood (10km)	0.019	0.022	0.018	0.020		0.0051	0.023
	(0.0040)***	(0.0036)***	(0.0037)***	(0.0035)***		(0.00079)***	(0.0036)***
Riots neighborhood (10-20km)			0.0046	0.0064		0.00072	0.0035
			(0.0018)**	(0.0016)***		(0.00045)	(0.0020)*
Log Riots neighborhood (10km)					0.13		
					(0.022)***		
Log Riots neighborhood (10-20km)					0.033		
					(0.015)**		
Log Urbanization; neighbor (10km radius)	-0.012	-0.047	-0.066	-0.061	-0.054	0.0029	-0.28
	(0.028)	(0.034)	(0.037)*	(0.030)**	(0.039)	(0.013)	(0.15)*
Log population 1831; neighbor (10km radius)	-0.10	-0.019	0.027	0.038	-0.037	-0.062	0.37
	(0.11)	(0.11)	(0.11)	(0.10)	(0.11)	(0.046)	(0.47)
Share of families in agriculture; neighbor (10km radius)	0.0036	0.0036	0.00089	0.0028	0.0045	-0.000077	-5.7e-06
	(0.0050)	(0.0055)	(0.0055)	(0.0048)	(0.0065)	(0.0018)	(0.023)
High wage, cereal; neighbor (10km radius)	-0.019	0.054	0.046	0.025	0.089	-0.047	0.32
	(0.038)	(0.11)	(0.11)	(0.11)	(0.12)	(0.037)	(0.91)
Low wage, dairy; neighbor (10km radius)	-0.033	-0.047	-0.044	-0.016	-0.045	0.032	-0.94
	(0.084)	(0.18)	(0.18)	(0.15)	(0.19)	(0.044)	(1.26)
Low wage, cereal; neighbor (10km radius)	0.31	0.065	-0.032	-0.24	0.16	0.14	-0.98
	(0.14)**	(0.26)	(0.27)	(0.25)	(0.30)	(0.060)**	(1.30)
Emp. share of agricultural workers; neighbor (10km radius)	0.0017	0.0027	0.0045	0.0014	0.0013	0.0026	0.028
	(0.0066)	(0.0071)	(0.0071)	(0.0060)	(0.0082)	(0.0020)	(0.030)
Emp. share for farmers/landowner; neighbor (10km radius)	-0.0015	-0.0041	-0.0016	-0.0046	-0.0045	-0.00046	-0.00080
	(0.0064)	(0.0069)	(0.0071)	(0.0054)	(0.0081)	(0.0022)	(0.035)
Emp. share in manufacturing; neighbor (10km radius)	0.0028	0.0036	0.0029	0.0014	0.0015	0.0018	0.030
	(0.0023)	(0.0028)	(0.0029)	(0.0027)	(0.0032)	(0.0012)	(0.016)*
Emp. share in trade and handicraft; neighbor (10km radius)	-0.013	-0.0013	0.0012	-0.00087	-0.0012	-0.0030	0.018
	(0.0057)**	(0.0061)	(0.0064)	(0.0057)	(0.0068)	(0.0026)	(0.030)
Emp. share of professionals; neighbor (10km radius)	0.0086	0.0088	0.0098	0.0031	0.0033	0.0020	0.029
	(0.0089)	(0.0099)	(0.010)	(0.0085)	(0.012)	(0.0034)	(0.050)
Emp. fractionalization; neighbor (10km radius)	-0.47	-0.23	-0.16	-0.047	-0.18	-0.12	1.47
	(0.32)	(0.33)	(0.35)	(0.35)	(0.40)	(0.12)	(1.88)
Farm labour - farmer ratio; neighbor (10km radius)	-0.015	-0.0060	-0.0067	-0.0035	-0.0056	-0.0025	0.010
	(0.0093)	(0.0085)	(0.0091)	(0.0080)	(0.011)	(0.0030)	(0.035)
Male share; neighbor (10km radius)	-0.0064	0.0020	0.00011	0.0050	0.0064	-0.0041	0.014
	(0.0083)	(0.0089)	(0.0091)	(0.0081)	(0.011)	(0.0035)	(0.041)
Any enclosure in parish before 1831; neighbor (10km radius)	0.23	-0.073	-0.11	-0.13	-0.23	-0.018	0.36
	(0.16)	(0.18)	(0.18)	(0.14)	(0.21)	(0.064)	(0.78)
Inequality; neighbor (10km radius)	-0.014	-0.0041	0.0095	0.014	-0.020	0.0018	0.017
	(0.012)	(0.013)	(0.015)	(0.012)	(0.015)	(0.0056)	(0.070)
Log middle class; neighbor (10km radius)	0.28	0.096	0.050	0.028	0.11	0.085	-0.27
	(0.12)**	(0.13)	(0.13)	(0.12)	(0.14)	(0.049)*	(0.49)
Near market (1 km); neighbor (10km radius)	0.072	0.068	-0.023	0.076	0.19	-0.14	-0.36
	(0.31)	(0.32)	(0.32)	(0.29)	(0.35)	(0.086)	(1.34)
Near coach stop (1 km); neighbor (10km radius)	0.036	0.038	0.095	0.046	-0.10	0.11	-1.09
	(0.30)	(0.34)	(0.35)	(0.30)	(0.37)	(0.096)	(0.96)
Petitions; neighbor (10km radius)	-0.015	-0.020	-0.016	-0.019	-0.017	-0.0048	-0.065
	(0.016)	(0.017)	(0.018)	(0.016)	(0.018)	(0.0076)	(0.099)
Near newspapers; neighbor (10km radius)	-0.27	-0.16	-0.16	-0.12	-0.21	-0.11	0.11
	(0.14)*	(0.15)	(0.15)	(0.14)	(0.18)	(0.060)*	(0.81)
Log distance to garrison; neighbor (10km radius)	-0.0030	0.090	0.089	0.094	0.11	0.011	-0.19
	(0.016)	(0.056)	(0.061)	(0.065)	(0.060)*	(0.029)	(0.28)
Near police force; neighbor (10km radius)	-0.037	0.25	0.27	0.27	0.39	0.038	4.43
	(0.19)	(0.22)	(0.24)	(0.25)	(0.25)	(0.073)	(1.26)***
const	0.0048	-1.28	-1.35	-1.47	-1.49	-0.024	-7.51
	(0.67)	(0.76)*	(0.79)*	(0.73)**	(0.91)	(0.30)	(3.69)**
Observations	10,326	9,258	9,258	9,258	9,258	9,258	9,258
R-squared	0.147	0.194	0.196	0.192	0.181	0.249	
Dummies	County	County	County	NO	County	County	County
Fundamentals	NO	YES	YES	YES	YES	YES	YES
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Cluster by par
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5 is an extension of table 3 that includes interactions between the spatial lag and own fundamentals. Our goal is to get a sense for how different fundamentals may have hindered or enabled the diffusion of riots. In particular, we can think of this specification as allowing the endogenous effect to be heterogeneous and to vary as a function of the parish-specific factors. It is evident from the results that there is a fair amount of heterogeneity: the interactions with urbanization and share of males have a negative sign, suggesting that urbanized areas and those with more men are less likely to experience riots as a result of being exposed to riots nearby. The fundamentals that make parishes more vulnerable are population, share of farmers to landowners, share of professionals, inequality, middle class, whether they have sent petitions to parliament, and whether they are far from garrisons.

A5: Fundamentals, diffusion and interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Riots	Riots	Riots	Riots	Riots	Riots(bin)	Riots
Riots neighborhood (10km)	-0.10	-0.14	-0.13	-0.099		-0.019	-0.11
	(0.051)**	(0.058)**	(0.061)**	(0.060)		(0.012)	(0.13)
Riots neighborhood (10-20km)			0.0030	0.0052		0.00059	0.0043
			(0.0014)**	(0.0013)***		(0.00041)	(0.0019)**
Log Urbanization x All riots near (10km)	-0.011	-0.0093	-0.0089	-0.010	-0.011	-0.0020	0.00064
	(0.0024)***	(0.0031)***	(0.0031)***	(0.0030)***	(0.0031)***	(0.00070)***	(0.0043)
Log population 1831 x All riots near (10km)	0.010	0.0075	0.0076	0.0086	-0.00043	0.00050	0.0048
	(0.0035)***	(0.0041)*	(0.0043)*	(0.0043)**	(0.0037)	(0.0016)	(0.012)
Share of families in agriculture x All riots near (10km)	0.00018	0.00017	0.00016	0.00014	0.00018	-0.000044	-0.00026
	(0.00020)	(0.00024)	(0.00024)	(0.00023)	(0.00025)	(0.000047)	(0.00027)
High wage, cereal x All riots near (10km)	-0.0047	-0.0048	-0.0065	-0.0029	-0.015	0.0042	-0.039
	(0.010)	(0.011)	(0.011)	(0.010)	(0.0099)	(0.0043)	(0.050)
Low wage, dairy x All riots near (10km)	-0.0059	-0.0061	-0.0069	-0.0054	-0.021	-0.0052	-0.12
	(0.010)	(0.010)	(0.011)	(0.0100)	(0.0093)**	(0.0037)	(0.035)***
Low wage, cereal x All riots near (10km)	0.011	0.0095	0.0073	0.0067	-0.0092	-0.0039	-0.14
	(0.011)	(0.011)	(0.012)	(0.011)	(0.0098)	(0.0036)	(0.034)***
Emp. share of agricultural workers x All riots near (10km)	0.000022	0.00017	0.00017	0.00013	0.000016	0.00010	0.0013
	(0.00020)	(0.00022)	(0.00022)	(0.00021)	(0.00017)	(0.000057)*	(0.00043)***
Emp. share for farmers/landowner x All riots near (10km)	0.00028	0.00035	0.00037	0.00035	0.00022	0.00020	0.0014
	(0.00016)*	(0.00015)**	(0.00015)**	(0.00012)***	(0.00019)	(0.000071)***	(0.00045)***
Emp. share in manufacturing x All riots near (10km)	0.000062	-0.00012	-0.00015	-0.00030	-0.00014	-0.000095	-0.00036
	(0.00022)	(0.00026)	(0.00025)	(0.00023)	(0.00026)	(0.00011)	(0.00097)
Emp. share in trade and handicraft x All riots near (10km)	-0.000100	-0.00019	-0.00017	-0.00015	-0.00052	-0.00013	0.00084
	(0.00032)	(0.00039)	(0.00041)	(0.00041)	(0.00032)	(0.000094)	(0.00069)
Emp. share of professionals x All riots near (10km)	0.0014	0.0016	0.0016	0.0016	0.0016	0.00018	0.0030
	(0.00030)***	(0.00033)***	(0.00032)***	(0.00032)***	(0.00039)***	(0.000074)**	(0.00064)***
Emp. fractionalization x All riots near (10km)	-0.030	-0.026	-0.025	-0.028	-0.043	-0.0024	0.053
	(0.025)	(0.024)	(0.024)	(0.024)	(0.016)***	(0.0048)	(0.035)
Farm labour - farmer ratio x All riots near (10km)	-0.00030	-0.00040	-0.00043	-0.00041	-0.00051	0.000024	-0.00010
	(0.00030)	(0.00045)	(0.00045)	(0.00044)	(0.00046)	(0.00011)	(0.00055)
Male share x All riots near (10km)	-0.0012	-0.0011	-0.0011	-0.0010	-0.0017	-0.00011	0.0013
					(0.00016)***	(0.00011)	(0.00083)
Enclosure before 1831 x All riots near (10km)	0.0048	0.0054	0.0052	0.0039	0.0057	-0.00034	-0.0047
	(0.0027)*	(0.0028)*	(0.0028)*	(0.0027)	(0.0027)**	(0.00086)	(0.0045)
Inequality x All riots near (10km)	0.00054	0.00080	0.00080	0.00081	0.00069	0.00011	0.0029
	(0.00027)**	(0.00042)*	(0.00042)*	(0.00042)*	(0.00039)*	(0.00011)	(0.00080)***
Log middle class x All riots near (10km)	0.014	0.015	0.015	0.014	0.022	0.0040	-0.00063
	(0.0036)***	(0.0044)***	(0.0046)***	(0.0047)***	(0.0049)***	(0.0016)**	(0.011)
Near market (1 km) x All riots near (10km)	0.025	0.020	0.020	0.019	0.021	0.00082	-0.00083
	(0.013)**	(0.015)	(0.014)	(0.014)	(0.015)	(0.0035)	(0.013)
Near coach stop (1 km) x All riots near (10km)	0.0055	0.0070	0.0066	0.0059	0.0068	0.0027	0.00026
	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)	(0.0035)	(0.012)
Petitions x All riots near (10km)	0.0052	0.0047	0.0047	0.0047	0.0048	0.00032	0.00068
	(0.0024)**	(0.0025)*	(0.0025)*	(0.0025)*	(0.0024)**	(0.00036)	(0.00083)
Near newspaper x All riots near (10km)	0.0073	0.0088	0.0080	0.0072	0.0091	0.0031	0.00058
	(0.0062)	(0.0068)	(0.0067)	(0.0065)	(0.0068)	(0.0034)	(0.0055)
Log distance to garrison x All riots near (10km)	0.0065	0.0094	0.0084	0.0059	0.0051	0.0019	0.0063
	(0.0020)***	(0.0024)***	(0.0026)***	(0.0022)***	(0.0012)***	(0.00075)**	(0.0058)
Near police force x All riots near (10km)	-0.0025	0.0011	-0.00030	0.0041	0.0023	0.0032	-0.00072
	(0.019)	(0.021)	(0.021)	(0.021)	(0.021)	(0.0043)	(0.020)
const	0.0031	0.53	0.44	0.067	-0.19	-0.011	-3.48
	(0.031)	(0.30)*	(0.32)	(0.29)	(0.24)	(0.12)	(1.89)*
Observations	9,266	9,266	9,266	9,266	9,266	9,266	9,266
R-squared	0.242	0.247	0.248	0.244	0.246	0.259	
County dummies	YES	YES	YES	NO	YES	YES	YES
Fundamentals	No	YES	YES	YES	YES	YES	YES
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Cluster by par
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	Poisson

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

C Appendix: additional panel results (not for publication)

Table A6 presents the summary statistics for the main variables used in the panel section.

A6: Panel summary stats

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Near fairs (10km)	405,760	0.18	0.52	0	14
Riots (weekly)	413,400	0.0054	0.12	0	15
Riots within 10kms (weekly)	413,400	0.16	1.25	0	88
Near coach stop (10 km)	413,400	0.63	0.48	0	1
Near newspaper (10 km)	413,400	0.22	0.41	0	1

This section presents some additional panel results. Table A7 presents results of panel regressions with fundamentals and county and week effects on riots. Focusing on column 5, we find that urbanization, population, share of families in agriculture, low wage in a cereal growing area, the share of professionals, the share of males, inequality, the size of the middle class, and having a market nearby are all significant.

A7: Fundamentals

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots
Log Urbanization	-0.0011	-0.0015	-0.0015	-0.0019	-0.0017
	(0.00021)***	(0.00023)***	(0.00026)***	(0.00036)***	(0.00036)***
Log population 1831	0.0041	0.0042	0.0046	0.0030	0.0030
	(0.00031)***	(0.00032)***	(0.00039)***	(0.00062)***	(0.00062)***
Share of families in agriculture	4.3e-06	0.000043	0.000050	0.000050	0.000051
	(0.000013)	(0.000023)*	(0.000024)**	(0.000024)**	(0.000024)**
High wage, cereal	0.0012	0.0012	0.0016	0.0015	0.0019
	(0.00076)	(0.00077)	(0.00075)**	(0.00075)**	(0.00090)**
Low wage, dairy	-0.0012	-0.0012	-0.0017	-0.0016	-0.0016
	(0.0013)	(0.0013)	(0.0012)	(0.0012)	(0.0012)
Low wage, cereal	0.011	0.011	0.011	0.011	0.011
	(0.0034)***	(0.0034)***	(0.0034)***	(0.0034)***	(0.0034)***
Emp. share of agricultural workers		-0.000015	-0.000013	-8.4e-06	-8.8e-06
		(0.000023)	(0.000025)	(0.000025)	(0.000025)
Emp. share of farmers/landowner		0.000043	0.000040	0.000036	0.000036
		(0.000027)	(0.000028)	(0.000028)	(0.000028)
Emp. share in manufacturing		-7.2e-06	-7.9e-06	-0.000017	-0.000018
		(0.000025)	(0.000026)	(0.000027)	(0.000027)
Emp. share in trade and handicraft		0.000099	0.00011	0.000018	0.000021
		(0.000023)***	(0.000025)***	(0.000042)	(0.000042)
Emp. share of professionals		0.00017	0.00016	0.00013	0.00013
		(0.000034)***	(0.000043)***	(0.000044)***	(0.000045)***
Farm labour - farmer ratio			6.0e-06	-1.5e-06	-3.0e-06
			(0.000052)	(0.000052)	(0.000052)
Male share			-0.00018	-0.00024	-0.00023
			(0.000052)***	(0.000056)***	(0.000056)***
Enclosed before 1831			0.00028	0.00025	0.00027
			(0.00049)	(0.00049)	(0.00049)
Inequality (tax / 1821 population)			0.000071	0.000055	0.000057
			(0.000013)***	(0.000013)***	(0.000013)***
Log middle class				0.0016	0.0015
				(0.00058)***	(0.00058)***
Near market (1 km)				0.0054	0.0057
				(0.0017)***	(0.0018)***
Near coach stop (1 km)				0.00098	0.0015
				(0.0017)	(0.0018)
Petitions 1828-31				0.00025	0.00025
				(0.00015)*	(0.00015)
Near newspapers				-0.00049	-0.00025
				(0.0011)	(0.0011)
Log distance to garrison					0.00040
					(0.00057)
Near police force (1km)					-0.0033
					(0.0019)*
Observations	386,760	386,600	370,640	370,640	370,640
R-squared	0.001	0.001	0.001	0.002	0.002
Fixed Effect	County	County	County	County	County
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.

We now move to a specification that more directly captures the time structure of the data. Furthermore, we introduce parish fixed effects, which is a natural way in which to capture all of the fixed factors in the data. Table A8 considers the above specification for different values of L. The spatial lag is introduced with several time lags in columns 1-5. These are all significant. It is also of interest that the impact of past spatial lags turns negative: a protest in a neighboring parish last week increases the incidence of riots, but one two weeks ago (or earlier) decreases it. A similar pattern emerges in columns 6-10, which consider own lags. Finally, columns 11-15 include both spatial and own lags. The impact of combining both is small.

A8: Diffusion without fundamentals

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots	(7) Riots	(8) Riots	(9) Riots	(10) Riots	(11) Riots	(12) Riots	(13) Riots	(14) Riots	(15) Riots
Riots neighbourhood (t-1)	0.0039	0.0040	0.0039	0.0039	0.0034						0.0029	0.0030	0.0030	0.0030	0.0030
	(0.00098)***	(0.00100)***	(0.00099)***	(0.00099)***	(0.00097)***						(0.00097)***	(0.00099)***	(0.00098)***	(0.00098)***	(0.00096)***
Riots neighbourhood (t-2)		-0.0012	-0.0012	-0.0012	-0.0017							-0.00077	-0.00069	-0.00071	-0.00069
		(0.00033)***	(0.00033)***	(0.00033)***	(0.00037)***							(0.00035)**	(0.00035)**	(0.00035)**	(0.00036)*
Riots neighbourhood (t-3)			-0.00076	-0.00070	-0.0011								-0.000090	-0.000023	-0.000030
			(0.00026)***	(0.00025)***	(0.00031)***								(0.00025)	(0.00024)	(0.00026)
Riots neighbourhood (t-4)				-0.00073	-0.0011									-0.000071	-0.000016
				(0.00030)**	(0.00033)***									(0.00025)	(0.00026)
Riots neighbourhood (t-5)					-0.0012										-0.000021
					(0.00027)***										(0.00018)
Riots neighbourhood (t-6)					-0.0012										0.000017
					(0.00026)***										(0.00017)
Riots neighbourhood (t-7)					-0.0011										0.00012
					(0.00027)***										(0.00020)
Riots neighbourhood (t-8)					-0.0015										-0.000018
					(0.00027)***										(0.00017)
Riots neighbourhood (t-10)					-0.0016										0.000030
					(0.00029)***										(0.00019)
Riots (t-1)						0.041	0.041	0.039	0.038	0.020	0.032	0.032	0.031	0.029	0.011
						(0.016)***	(0.016)**	(0.016)**	(0.016)**	(0.016)	(0.016)**	(0.016)*	(0.016)*	(0.016)*	(0.016)
Riots (t-2)							-0.017	-0.017	-0.019	-0.035		-0.016	-0.016	-0.017	-0.034
							(0.0062)***	(0.0062)***	(0.0062)***	(0.0069)***		(0.0065)**	(0.0065)**	(0.0065)***	(0.0070)***
Riots (t-3)								-0.022	-0.022	-0.037			-0.021	-0.022	-0.037
								(0.0052)***	(0.0052)***	(0.0063)***			(0.0054)***	(0.0054)***	(0.0064)***
Riots (t-4)									-0.022	-0.036				-0.021	-0.036
									(0.0049)***	(0.0059)***				(0.0049)***	(0.0058)***
Riots (t-5)										-0.040					-0.040
										(0.0060)***					(0.0059)***
Riots (t-6)										-0.042					-0.042
										(0.0053)***					(0.0052)***
Riots (t-7)										-0.043					-0.044
										(0.0052)***					(0.0051)***
Riots (t-8)										-0.045					-0.045
										(0.0053)***					(0.0052)***
Riots (t-9)										-0.044					-0.044
										(0.0055)***					(0.0055)***
Riots (t-10)										-0.049					-0.050
										(0.0057)***					(0.0056)***
Observations	403,065	392,730	382,395	372,060	310,050	403,065	392,730	382,395	372,060	310,050	403,065	392,730	382,395	372,060	310,050
R-squared	0.001	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003	0.014	0.002	0.003	0.003	0.004	0.015
Fixed effect	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish	Parish
Week FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley	Conley

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Our assumption is that the correlated and contextual effects can be picked up by the fixed effects, since they are assumed fixed. But our specification also includes week effects, and so also controls for shocks in fundamentals that are common across space. We can explore this possibility in more detail by including more specific time effects that allow shocks to vary across space and time. In particular, week effects interacted with agricultural regions and county effects interacted with a post-23 November 1830 dummy. The first controls for weekly shocks that are constant within agricultural region. For a shock not to be captured it would need to affect only some parishes within an agricultural region. The second controls for a specific time shock - the changes in national policy that followed after 23 November 1830 - and allows them to vary by county. For a shock not to be fully captured it must then affect parishes within a county differentially.[62]

Table A9 presents the results of regressions where we have added a set of controls that allow for differential time shocks across units of observation. In columns 1-4 we present results for a specification that adds interactions between agricultural region and week for the week dummies. This specification allows different agricultural regions to experience different temporal (weekly) shocks. The results are in columns 1-4. Column 4, for example, can be compared with column 13 of table A8. Although the coefficients are now smaller, the difference is not substantial. Significance and sign patters remain unchanged. We also use an alternative measures that interact countries with a dummy that captures the post- 23rd November 1830 period (for reasons explained in the historical

[62]A natural specification to consider would be a set of county x week interactions, but this generates a large number of dummies that we cannot estimate precisely. This is because although we have a large number of observations, those exhibiting variation over time are more restricted.

section). Again the coefficients are slightly different, but the overall message is the same. The fact that results change so little suggests that there is not much variation left once we have controlled for parish and week effects.

A9: Diffusion
fundamentals and time trends

VARIABLES	(1) Riots	(2) Riots	(3) Riots	(4) Riots	(5) Riots	(6) Riots
Riots neighbourhood (t-1)	0.0027		0.0019	0.0050		0.0041
	(0.00090)***		(0.00090)**	(0.0010)***		(0.0010)***
Riots neighbourhood (t-2)			-0.0012			-0.00024
			(0.00038)***			(0.00036)
Riots neighbourhood (t-3)			-0.00041			-0.000011
			(0.00027)			(0.00027)
Riots (t-1)		0.037	0.030		0.045	0.031
		(0.016)**	(0.016)*		(0.016)***	(0.017)*
Riots (t-2)			-0.016			-0.016
			(0.0065)**			(0.0065)**
Riots (t-3)			-0.021			-0.021
			(0.0054)***			(0.0054)***
Observations	403,065	403,065	382,395	403,065	403,065	382,395
R-squared	0.001	0.001	0.003	0.002	0.002	0.004
Fixed effect	Parish	Parish	Parish	Parish	Parish	Parish
Week FE	YES	YES	YES	YES	YES	YES
Time trend	Agricultural region x week	Agricultural region x week	Agricultural region x week	County x post 23 Nov	County x post 23 Nov	County x post 23 Nov
Standard errors	Conley	Conley	Conley	Conley	Conley	Conley

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A10 reports the results for two different specifications of the spatial and own lag of riots. The interactions capture how a parish's fundamentals affect how it responds to riots in its vicinity. For example, we find that in parishes that are more urbanized the impact of riots nearby on own riots is smaller. This means that own urbanization deters contagion. We also find that being a high wage cereal area reduces contagion.[63] On the other hand, the share of professionals, the size of the middle class, and the number of newspapers increase contagion, suggesting that middle class characteristics might play a role in diffusion. Interestingly, the measures of repression, distance to the nearest garrison and whether there is a police force have no clear impact on contagion.

[63] The way to think of the high wage cereal is relative to the omitted category, which in this case is (high wage, dairy).

A10: Diffusion with interactions (and fixed effects)

VARIABLES	(1) Riots	(2) Riots
Riots neighbourhood (t-1)	-0.015 (0.022)	-0.010 (0.023)
Riots neighbourhood (t-2)		-0.00072 (0.00037)*
Riots neighbourhood (t-3)		-0.000095 (0.00028)
Riots (t-1)		0.018 (0.018)
Riots (t-2)		-0.017 (0.0068)**
Riots (t-3)		-0.021 (0.0057)***
Log Urbanization x All riots near (10km) at (t-1)	-0.0017 (0.00093)*	-0.0016 (0.00093)*
Log population 1831 x All riots near (10km) at (t-1)	0.0030 (0.0018)*	0.0027 (0.0017)
Share of families in agriculture x All riots near (10km) at (t-1)	0.000060 (0.000069)	0.000057 (0.000071)
High wage, cereal x All riots near (10km) at (t-1)	-0.0083 (0.0036)**	-0.0086 (0.0036)**
Low wage, dairy x All riots near (10km) at (t-1)	-0.0035 (0.0039)	-0.0039 (0.0039)
Low wage, cereal x All riots near (10km) at (t-1)	-0.0019 (0.0039)	-0.0024 (0.0039)
Emp. share of agricultural workers x All riots near (10km) at (t-1)	0.000095 (0.000069)	0.000085 (0.000069)
Emp. share for farmers/landowner x All riots near (10km) at (t-1)	0.00015 (0.000086)*	0.00014 (0.000087)
Emp. share in manufacturing x All riots near (10km) at (t-1)	0.000067 (0.00011)	0.000056 (0.00011)
Emp. share in trade and handicraft x All riots near (10km) at (t-1)	0.000025 (0.00011)	0.000014 (0.00011)
Emp. share of professionals x All riots near (10km) at (t-1)	0.00042 (0.00019)**	0.00039 (0.00019)**
Farm labour - farmer ratio x All riots near (10km) at (t-1)	0.000016 (0.00011)	0.000021 (0.00011)
Male share x All riots near (10km) at (t-1)	-0.00022 (0.00018)	-0.00019 (0.00018)
Enclosures before 1831 x All riots near (10km) at (t-1)	-0.0023 (0.0015)	-0.0025 (0.0015)*
Inequality x All riots near (10km) at (t-1)	0.000051 (0.000053)	0.000038 (0.000052)
Log middle class x All riots near (10km) at (t-1)	0.0026 (0.0014)*	0.0025 (0.0014)*
Near market (1 km) x All riots near (10km) at (t-1)	0.00071 (0.0041)	0.00031 (0.0042)
Near coach stop (1 km) x All riots near (10km) at (t-1)	-0.0024 (0.0045)	-0.0021 (0.0045)
Petitions x All riots near (10km) at (t-1)	0.00025 (0.00092)	0.00015 (0.00091)
Near newspaper x All riots near (10km) at (t-1)	0.012 (0.0063)*	0.012 (0.0064)*
Log distance to garrison x All riots near (10km) at (t-1)	-0.00064 (0.0013)	-0.00081 (0.0013)
Near police (1km) x All riots near (10km) at (t-1)	0.0054 (0.0056)	0.0053 (0.0055)
Observations	361,374	342,842
R-squared	0.004	0.005
Fixed effect	Parish	Parish
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.