



Rationalizing protests – From individuals to networks[☆]

Tim Baule^{*}, Jonathan Bothner, Maximilian Kähny

University of Bayreuth, Faculty of Law, Business and Economics, Bayreuth, Germany

ARTICLE INFO

Keywords:

Collective action
Public protests
Network effects
Social networks

ABSTRACT

We consider a theoretical model of network goods to explain protest participation. The model distinguishes between two equilibria: (i) when network effects are weak, individual participation is primarily driven by standalone benefits; (ii) when network effects are strong, expectations about others' participation become crucial. Using survey data from the American National Election Studies, we estimate a spatial autoregressive model and identify both standalone and network benefits through direct and indirect effects. Our findings reveal significant spillover effects in protest participation across individuals. Specifically, we identify both types of benefits for the full United States sample as well as within more homogeneous subgroups. Across subgroups, protest dynamics are predominantly shaped by strong network effects. These estimation results, in combination with the model's implications, offer new insights into the scale of contemporary protest movements in the United States.

1. Introduction

PUBLIC PROTESTS have been a vital force for citizens to express their discontent in the public sphere worldwide. The act of demonstrating – whether peaceful or violent – calls for policies, reforms, or even a change of government, and drives social and political change not only in democracies but also in authoritarian regimes. For instance, rallies that later became known as the Yellow Vest Protests arose in France from late 2018 until early 2019, when diesel prices increased by approximately 23% over 12 months, as the [BBC \(2018\)](#) reported.¹ With the ensuing riots drawing the participation of 282,000 protesters at its peak, the Yellow Vest Protests ultimately forced the French government to concede by announcing a halt on planned fuel tax increases and freezing electricity and gas prices for 2019. The economic damage of these civil outbursts amounted to 0.2 percentage points of quarterly growth – approximately 5 billion euros – according to [Reuters \(2019\)](#),² and was commented on by the Finance Minister of France, Bruno Le Maire, with these words:

“It’s a catastrophe for business, it’s a catastrophe for our economy.” —
BBC, 2018

[☆] We thank Geoffrey Castillo, Fabian Herweg, Henrik Gühling, Martin Leschke, two anonymous referees, as well as participants at the Public Choice Conference 2025, University of Bayreuth Graduate Seminar 2024, Bavarian Micro Day 2024, and the Jahrestagung des Ausschusses für Wirtschaftssysteme und Institutionenökonomik 2024 for helpful comments and suggestions. We further thank the American National Election Studies for data access.

^{*} Corresponding author.

Email addresses: tim.baule@uni-bayreuth.de (T. Baule), jonathan.bothner@uni-bayreuth.de (J. Bothner), maximilian.kaehny@uni-bayreuth.de (M. Kähny).

¹ “Yellow vest protests ‘economic catastrophe’ for France”, BBC, December 9, 2018, <https://www.bbc.com/news/world-europe-46499996>, last accessed: May 5, 2024.

² “French ‘Yellow Vest’ protests cost 0.2 percentage points of growth - Le Maire”, Reuters, February 28, 2019, <https://www.reuters.com/article/idUSKCN1QH170/>, last accessed: May 5, 2024.

Considering the far-reaching implications of mass mobilization like the Yellow Vest Protests, the question arises: what precise dynamics unfold behind protests? In this study, we investigate the factors driving individual protest decisions, drawing from a standard model of a single network good. In particular, we focus on how network effects influence individual participation and how these effects translate into aggregate outcomes.

On the individual level, one rationale for participating in a protest is deriving protest-dependent utility by either satisfying a sense of moral duty or benefiting from an underlying objective. While both causes seem plausible, two issues related to the latter must be mentioned. First, most protests are directed toward the greater good of the public, leading to the classic free-rider problem among potential participants (Apolte, 2012; Olson, 1971). The second issue is related to the paradox of voting. It is present even if the free-rider problem is disregarded: with the individual's participation being non-pivotal in achieving the underlying objective of the protest, the cost of participation should outweigh the benefit of contribution (Downs, 1957). This cost is particularly substantial in the case of protests since, depending on the context or country, individuals might face not only minor transportation and opportunity costs, but also severe repercussions like physical violence, incarceration, torture, and death.

A more recent literature focuses on the role of networks in explaining individual participation decisions in protests. Similar to decisions regarding network goods, like joining a social media platform, an individual's value from protesting is assumed to increase as more people join (Economides, 1996). This insight originates in the seminal work of Kuran (1989) and Granovetter (1978), who emphasize interdependencies among protesters and analyze their implications for collective action. Such network effects can be understood as direct and indirect benefits an individual gains from participating, which increase as the network attracts further participants. In the context of protests, network benefits include peer effects through social ties. These peer effects may stem from social utility obtained from friendships made or maintained through joint participation in protest events (Bursztyn et al., 2021). They may also be the result of an individual signaling compliance with social norms to their peers to avoid social sanctions (Enikolopov et al., 2020b), a mechanism that has also been emphasized in the related literature on voting behavior (Gerber et al., 2008; DellaVigna et al., 2016). Larger protests will also attract more media coverage, which can further amplify these social incentives (Enikolopov et al., 2020a). However, the realization of these network benefits crucially depends on others' participation. The individual's decision to participate is thus determined by their *ex ante* expectation about the protest. While Carter and Carter (2020) and Truex (2019) identify focal points as a mechanism to increase individual expectations about protest size, the general problem of coordination remains.

Combining these well-known insights – (1) the individual's utility from participating is subject to protest-dependent attitudes; (2) the individual's participation is non-pivotal to achieving the protest objective; (3) networks affect the individual's participation decision while allowing for multiple equilibria due to coordination problems – we formalize a single theoretical framework and empirically test its implications. The model is in that way a formalization of network dependencies classical to models of protest coordination and theory of revolutions as established by Kuran (1989) and Granovetter (1978). In the framework, we consider a continuum of heterogeneous individuals whose utility from protesting consists of two components: (i) the interaction between an individual's type and the standalone benefit, and (ii) the network benefit that increases with the expected number of protest participants. Following the rational-expectation approach in the static model, we derive equilibrium outcomes for protest participation depending on the relation between the standalone and the network benefit. If the standalone benefit exceeds the network benefit, which we define as *weak network effects*, a unique equilibrium exists for any exogenous participation cost. If the network benefit exceeds the standalone benefit, which we define as *strong network effects*, two stable equilibria coexist for intermediate participation costs, namely the extreme outcomes of full and no participation. This result highlights the coordination problem individuals face when deciding to attend a protest, for which the network benefit is the determining factor for participation. In the dynamic version of the model, we further show the precise adjustment processes of protest participation over discrete time, which lead to the same outcomes in the limiting case as in the static model.

Based on this theoretical framework, we present descriptive empirical evidence on the relative influence of standalone and network benefits on the decision to protest, thereby quantifying effects introduced in the literature by authors such as Granovetter (1978) and Kuran (1989). We use data on more than 6000 individual respondents from the American National Election Studies (ANES) 2020 survey wave (ANES, 2021). In a robustness check, we use the 2016 survey wave. We first test the hypotheses (i) that the standalone benefit determines an individual's protest participation and (ii) that the network benefit determines an individual's protest participation. The spatial structure of our model then allows us to compare direct and indirect effects of the covariates on the decision to protest. From this comparison, we draw conclusions about the relative magnitudes of standalone and network benefits. We go on to explore heterogeneity in these findings across different political groups and protest movements.

The main empirical challenges consist of identifying standalone and network benefits and clustering individuals according to their political attitudes. Incorporating individuals' participation decisions within a social network into a simple ordinary least squares (OLS) regression leads to endogeneity due to the inherent interdependencies among them. Individual A's protest decision affects individual B's protest decision and vice versa. Hence, regressing individual A's protest decision on individual B's protest decision leads to simultaneity in the equation, resulting in biased and inconsistent estimates. To overcome this problem, we rely on a generalized spatial two-stage least squares (GS2SLS) estimator proposed by Drukker et al. (2013), in which the protest decisions of an individual's social network are instrumented by their individual characteristics. The standalone and network benefits are measured by interpreting the direct and indirect effects of a set of covariates. To explore heterogeneity across different societal groups, we rely on the clustering algorithm proposed by Kaufman and Rousseeuw (2009) for political groups and a decision rule for more granular protest groups.

The results from the baseline regression suggest that both the standalone and network benefits are driving forces behind individual protest decisions. To explore heterogeneity, we divide individuals into three clusters based on their political opinions. These clusters can be interpreted as groups of individuals within the sample holding left-leaning, moderate, and right-leaning political views. We

find that the standalone and network benefits are significant determinants of the protesting decision within each cluster, though with varying magnitudes. Interestingly, network benefits seem to dominate standalone benefits for all clusters.

In a finer-grained specification, we pool individuals based on causes they consider important and identify four relevant potential protest movements: Black Lives Matter (BLM), healthcare, environment, and pro-immigration (these clusters are no longer mutually exclusive). We find strong network effects across all four protest movements. In an extension, we consider the model framework in combination with these benefit compositions to provide an explanation for their observed protest sizes.

This paper contributes to the literature by providing a better understanding of the determinants of protest participation. Drawing on a model of network goods applied to the context of protests, we find empirical evidence for the important role of network effects alongside standalone benefits in individuals' decisions to participate in protests. Specifically, we can disentangle individual-level effects from network-related effects and make statements about their relative influences. Methodologically, we contribute to the existing literature by employing a spatial identification strategy that involves building a synthetic network of United States (US) citizens. To the best of our knowledge, this approach to identifying network effects is novel to the protest literature.

The paper is structured as follows. After discussing the related literature in the following paragraphs, we introduce the framework in Section 2. In Section 2.1, we derive the potential equilibria of protest participation under strong and weak network effects in the static model. Next, we enrich the model by including discrete time in Section 2.2, deriving the precise protesting processes under weak and strong network effects. Thereafter, in Section 2.3, we formulate two hypotheses based on the model's implications. In Section 3, we introduce the empirical identification strategy used to test our hypotheses. The subsequent Section 4 presents the results for a baseline regression, as well as for political clusters in Section 4.2 and protest-specific clusters in Section 4.3. Finally, we conclude in Section 5. All proofs, additional figures, and tables are deferred to Appendices A.1–A.3, respectively.

Related literature

Acemoglu and Robinson (2001, 2005) establish a first game-theoretic, formal model on the occurrence of protests by considering distribution battles among the population as the primary cause of protests and potential subsequent revolutions. Disadvantaged citizens utilize protests and the threat of revolution to pressure elites into creating a more equal distribution of wealth and income. These elites, who run the state, act under a revolution constraint that allows them to strategically distribute resources. According to the authors, protests and revolutions occur when elites fail to adhere to the revolution constraint, and disadvantaged citizens respond by raising their voices via protests. This theoretical perspective aligns with the broader framework introduced by Gurr (1970), who attributes the origins of protest to relative deprivation, defined as the perceived gap between expected and actual conditions.

The approach formulated by Gurr (1970) has been challenged by several scholars who emphasize the role of mobilizing resources as the primary driver of protest mobilization (McCarthy and Zald, 1977; Zald et al., 1987; Jenkins, 1983). Mobilizing resources are broadly defined as the tangible and intangible assets available to groups for coordination and collective action. Within this literature, particular emphasis is placed on organizational structures as key mechanisms enabling collective engagement in protest (e.g., Edwards et al., 2018). A similar point was made as a response to Acemoglu and Robinson (2001, 2005), as some authors see an inconsistency between the explanation of Acemoglu and Robinson (2001, 2005) and fundamental insights from Olson's (1971) Theory of Collective Action (Egorov and Sonin, 2024; Apolte, 2012). In particular, Apolte (2012) claims that inequality among a nation's citizens is neither sufficient nor necessary for enlarged protests or revolutions. Instead, the ability to overcome the free-rider problem should explain protest events and revolutions.

The fundamental conflict between these two strands of theoretical literature emerges due to the different characterization of the underlying objective of protests: *club good vis-à-vis public good*. Under the notion of a club good, citizens protest to benefit from expected political changes (e.g., Acemoglu and Robinson, 2001, 2005). In contrast, under the assumption that the protest objective is characterized as a public good, the benefits from political changes are distributed among all citizens, regardless of the individual participation decision. Consequently, individuals would decide to free-ride – i.e., not protest – if the participation cost is sufficiently high. We do not impose any characterization on the nature of protests or the outcome. Instead, the microfoundation of our model is related to the literature on the voting paradox, which states that the individual's action is non-pivotal to the success of the underlying objective (Downs, 1957). This approach allows us to consider an individual's choice for protesting as the choice for a single network good, where protest participation is driven by a standalone and a network benefit. Thus, the conception of our model is also closely related to the industrial organization literature addressing network effects (Belleflamme and Peitz, 2015; Economides, 1996).

Later developments in the protest literature acknowledge how central the coordination problem is for explaining protests. This literature focuses on informational aspects, as, for example, Ellis and Fender (2011) extend the model from Acemoglu and Robinson (2001, 2005) by introducing information transmission via informational cascades based on a model proposed by Lohmann (1994). This informational exchange facilitates coordination. Another approach to overcoming the coordination problem is proposed by De Mesquita (2010), who models a difference in the timing of movements. The model relies on a protest vanguard that moves first, thereby shaping the movement's trajectory. This move is observed by other citizens, who can subsequently join the protest. Both models incorporate informational exchange as a device for switching from a low to a high participation equilibrium. However, they maintain a club good characterization of protests, which makes them prone to the above-mentioned criticism, too. In our proposed model, we incorporate the presented informational aspects via expectation formation. In particular, in the dynamic specification, informational cascades are modeled explicitly, and we provide an account of the pace at which they materialize.

In this regard, our paper is based on the theoretical literature that centers on threshold models of collective behavior, as introduced by Granovetter (1978). In this framework, individuals choose to participate in collective actions – such as protests – when the number of prior participants exceeds a certain threshold. This idea provides a behavioral microfoundation for how participation cascades can

emerge from heterogeneous individual preferences. Building on this, [Wiedermann et al. \(2020\)](#) present a network-based extension of Granovetter's model, showing how individual thresholds interact with social network structures to produce tipping points in protest dynamics. These models emphasize how even small shifts in expectations or participation can lead to rapid, large-scale mobilization, offering a complementary perspective to coordination-based and network benefit approaches.

Our paper is closely related to the work of [Kuran \(1989\)](#), who proposes a model in which revolutionary dynamics are driven by a threshold mechanism. In this model, individuals' privately held preferences regarding the regime or the opposition may diverge from their publicly expressed preferences. The utility an individual receives from expressing a preference depends on the expected share of other individuals supporting the regime (or the opposition) and on integrity costs incurred from expressing preferences that differ from privately held preferences. Due to the interdependence of public preferences, a shock that changes expectations of expressed preferences can set off a bandwagon, leading to more individuals finding it preferable to adapt their public stance, which may culminate in revolution. [Kuran's \(1989\)](#) insight that multiple equilibria exist when individuals' protesting decisions are interdependent is reflected in this paper.

Lastly, one recent strand of literature discusses the formation and effects of networks in overcoming the free-rider problem. The fundamental insight is that protest participation among social peers is strategically complementary. Such effects are identified by [Bursztyn et al. \(2021\)](#) in a field study with incentivized students in Hong Kong's anti-authoritarian protests and by [Enikolopov et al. \(2020a\)](#) using a natural experiment with social media data in Russia. Importantly, these approaches are capable of explaining protest participation irrespective of whether the desired outcome is a club good or a public good. We aim to contribute to this literature by preserving the central role of networks in overcoming the free-rider problem while explicitly modeling the strategic complementarity and testing its resulting hypotheses with a spatial model. The spatial model is a promising technique for identifying network effects, as highlighted by [Souza \(2024\)](#), and, to the best of our knowledge, has not been applied in the protest literature so far. Thereby, we provide complementary evidence in favor of [Bursztyn et al. \(2021\)](#) and [Enikolopov et al. \(2020a\)](#) while also contributing to the question of whether protest participation is a strategic complement or substitute as discussed by [Cantoni et al. \(2019\)](#) and [Shadmehri \(2021\)](#).

2. The framework

2.1. Static model

To establish the baseline model for participation in demonstrations, we follow the textbook approach by [Belleflamme and Peitz \(2015\)](#) on markets for a single network good.³ Consider an economy with a continuum of heterogeneous individuals of mass 1. Each individual decides whether to participate in the demonstration ($d = 1$) or not ($d = 0$), such that the action set is $d \in \{0, 1\}$. If an individual protests, the individual's utility is given by

$$U_1(\theta) = \theta a + v n^e - c, \quad (1)$$

where the individual's type θ is uniformly distributed on the interval $[0, 1]$. The utility from demonstrating consists of two components: (i) the interaction between the individual's type and the standalone benefit $a > 0$, which can represent but is not limited to a feeling of moral obligation, sympathy for the protest, or the benefit of the potential policy implementation; and (ii) the network benefit $v > 0$, which, for simplicity, increases linearly with the expected number of participants n^e . This network benefit can encompass both direct effects (e.g., social status, identification with a movement) and indirect effects (e.g., larger venues, media representation). Participation comes at a non-monetary cost $c > 0$, capturing opportunity costs or personal repercussions. If the individual decides not to protest ($d = 0$), the individual receives the outside option

$$U_0 = \underline{U}, \quad (2)$$

where, without loss of generality, we assume that the outside option is normalized to zero.⁴

For a given participation cost c and an expected network size n^e , the individual being indifferent between demonstrating or not is characterized by

$$\theta a + v n^e - c \geq 0, \quad (3)$$

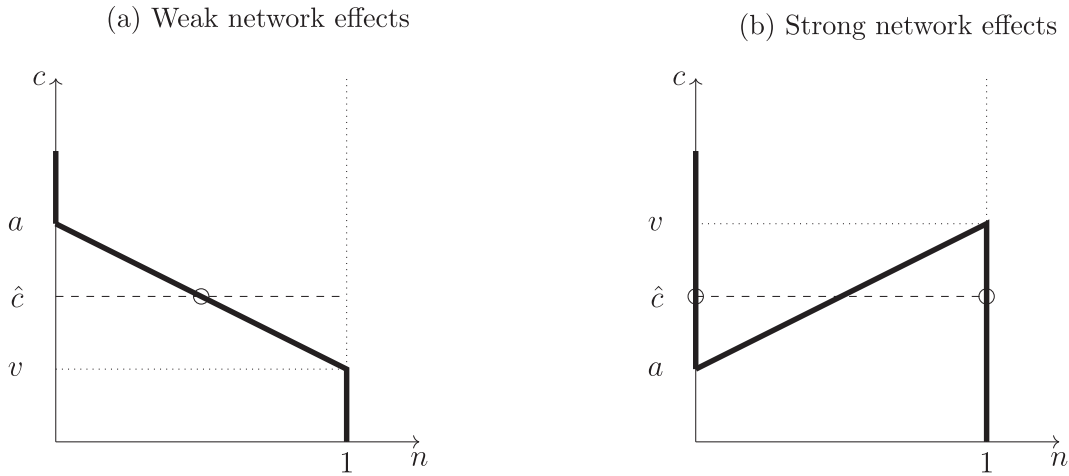
where

$$\theta \geq \frac{c - v n^e}{a} := \hat{\theta} \quad (4)$$

denotes the critical type threshold, i.e., individuals with types lower than $\hat{\theta}$ choose not to participate.

³ A related version of the model is put forward by [Economides \(1996\)](#) in the industrial organization literature. Regarding the literature on protests and revolutions, there is a large number of models that take insights from [Granovetter \(1978\)](#) and [Kuran \(1989\)](#) and model protest as a network-dependent decision.

⁴ In [Appendix A.1](#), we show that incorporating a non-zero outside option—which can reflect free-riding incentives—has no qualitative effect on the equilibrium outcome.

Fig. 1. Equilibria under weak and strong network effects for given cost $\hat{c}$.

Restricted to the outcome of no or full participation if $\hat{\theta}$ is not in the interval $[0, 1]$, the actual number of individuals demonstrating is

$$n(c, n^e) = \begin{cases} 0 & \text{if } n^e < (c - a)/v, \\ 1 - \frac{c - vn^e}{a} & \text{if } (c - a)/v \leq n^e \leq c/v, \\ 1 & \text{if } n^e > c/v. \end{cases} \quad (5)$$

We follow the rational-expectation approach to continue the analysis: if individuals form rational expectations in equilibrium, it must be that $n^e = n$. From the demand function in (5), it is straightforward that equilibria of no or full participation occur if either $c > a$ (nobody participates with $n = n^e = 0$) or if $c < v$ (everyone participates with $n = n^e = 1$). It follows that both equilibria coexist if $v > a$. Furthermore, the interior equilibrium with $0 < n^e = n < 1$ is

$$n(c) = \frac{a - c}{a - v}. \quad (6)$$

First, suppose we are in the scenario where the standalone benefit exceeds the benefit of the network, $v < a$, which we define as *weak network effects*. In that case, the number of participants $n(c)$ is a decreasing function of the cost incurred. Thus, there is a unique participation level for any (exogenous) cost c : $n = 0$ for $c > a$, $n = (a - c)/(a - v)$ for $v \leq c \leq a$, and $n = 1$ for $c < v$.

Second, suppose we are in the scenario where the benefit of the network exceeds the standalone benefit, $v > a$, which we define as *strong network effects*. In that case, the number of participants is an increasing function of the cost incurred. As an intuition, the marginal willingness to incur costs increases with a marginal increase in participation numbers. Furthermore, there coexist three rational-expectations equilibria for intermediate costs ($a < c < v$): $n = 0$, $n = (c - a)/(v - a)$, and $n = 1$. By the argument of a dynamic adjustment process, i.e., a marginal cost increase (decrease) drives the equilibrium towards full (no) participation, we can disregard the unstable interior equilibrium (see Rohlfs, 1974). In contrast, the two remaining equilibria depict precisely the coordination problem individuals face when deciding on a protest for which the network benefit v is the determining participation factor. While both equilibria are stable, it is straightforward that by following the Pareto criterion, the no-participation equilibrium ($n = 0$) is Pareto-dominated: each individual would be better off coordinating to end up in the $n = 1$ equilibrium.

An example of the potential equilibria, i.e., the unique equilibrium under weak network effects and the multiple equilibria under strong network effects, for an exogenous cost $\hat{c}$ is depicted in Fig. 1.

We can now characterize the following equilibria.

Proposition 1 (Static Network effects). *In equilibrium, the number of individuals participating in the demonstration*

(i) *under weak network effects ($v < a$) is denoted by*

$$n(c) = \begin{cases} 0 & \text{if } c > a, \\ \frac{a - c}{a - v} & \text{if } v \leq c \leq a, \\ 1 & \text{if } c < v; \end{cases} \quad (7)$$

(ii) *under strong network effects ($v > a$) is denoted by*

$$n(c) = \begin{cases} 0 & \text{if } c > v, \\ 0 \vee 1 & \text{if } a \leq c \leq v, \\ 1 & \text{if } c < a. \end{cases} \quad (8)$$

Conveying [Proposition 1](#) to the real world, weak network effects may relate to protests about topics tied to goods (policies) and personal goals rather than social conditions and norms. Examples would be union wage talks, farmers' protests, or gun control, where the standalone benefit of the good, a , is the participant's priority, and higher private costs arguably lead to fewer participation numbers.

Examining the theoretical underpinnings of strong network effects in the context of protest participation, the BLM Movement, the 2020–2021 Belarusian Protests, and the Iranian Women's Rights Movement may be compelling examples. Despite the potential for high personal repercussions, these movements demonstrate how network effects can be powerful enough to motivate more individuals to participate (as long as the cost satisfies $c \leq v$). Furthermore, the coordination problem that arises under strong network effects, with its two stable corner equilibria, provides a theoretical foundation for the concept of focal points: despite no inherent structural change, there can be an equilibrium switch from no participation ($n = n^e = 0$) to full participation ($n = n^e = 1$) when instances, e.g., the killing of George Floyd, lead to higher expectations for protest.

2.2. Dynamic model

To further analyze individuals' protest participation and its underlying processes, consider now the dynamic version of the model in discrete time $t \geq 1$, where the utility from demonstrating ($d = 1$) is given by

$$U_{1,t}(\theta) = \theta a + v n_t^e - c. \quad (9)$$

For simplicity, assume adaptive expectations, where the expected number of participants at time t is the actual number of participants from the previous period with $n_t^e = n_{t-1}$, and that the initial participation level is exogenous with $n_0 \in [0, 1]$.⁵ Holding the outside option fixed ($d = 0$) and normalized to $\underline{U}_{0,t} = 0 \ \forall \ t \geq 1$, the critical type threshold at time t denotes

$$\theta = \frac{c - v n_{t-1}}{a} := \hat{\theta}_t, \quad (10)$$

where the number of participants is $n_t = 1 - \hat{\theta}_t$.

We can then show the following.⁶

Proposition 2 (Dynamic Network effects). *The number of individuals participating in the demonstration at time $t \geq 1$ evolves according to*

$$n_t(c, n_0) = \begin{cases} 0 & \text{if } n_0 < \frac{c-a}{v}, \\ n_0 \left(\frac{v}{a}\right)^t + \left(1 - \frac{c}{a}\right) \sum_{i=0}^{t-1} \left(\frac{v}{a}\right)^i & \text{if } \frac{c-a}{v} \leq n_0 \leq \frac{c}{v}, \\ 1 & \text{if } n_0 > \frac{c}{v}, \end{cases} \quad (11)$$

where in the interior, the change in the number of participants per period is defined by

$$n_t - n_{t-1} = \left(\frac{v}{a}\right)^{t-1} (n_1 - n_0) := \Delta_t. \quad (12)$$

Thus,

(i) under weak network effects ($v < a$), the number of participants converges to

$$\lim_{t \rightarrow \infty} n_t(c, n_0) = \frac{a-c}{a-v}; \quad (13)$$

(ii) under strong network effects ($v > a$), the number of participants converges to

$$\lim_{t \rightarrow \infty} n_t(c, n_0) = \begin{cases} 0 & \text{if } n_0 < \frac{c-a}{v-a}, \\ 1 & \text{if } n_0 > \frac{c-a}{v-a}. \end{cases} \quad (14)$$

Proposition 2 highlights the outcome of protest participation under weak and strong network effects, subject to the adjustment process in protest participation per period. [Eq. \(11\)](#) states that protests where the initial protest size is characterized by full (no) participation remain at this extreme outcome. In contrast, protests where the initial participation number satisfies the interval $(c-a)/v \leq n_0 \leq c/v$ follow the dynamic adjustment process in [Eq. \(12\)](#): Under weak network effects ($v < a$), the change in protest participation, Δ_t , decreases per period, and the protest size ultimately converges to its interior limit $(a-c)/(a-v)$. With the standalone benefit being the determinant factor of protest participation, the marginal benefit of one more individual joining the protest on the critical type $\hat{\theta}_t$ exactly outweighs the individual's participation cost. Under strong network effects ($v > a$), the change in protest participation, Δ_t , increases per period. Here, the limit outcome of the protest size crucially depends on its initial participation number n_0 , where [Eq. \(14\)](#) shows that the protest size drives to the full (no) participation equilibrium if $n_0 > (c-a)/(v-a)$ (if $n_0 < (c-a)/(v-a)$).

⁵ The assumption of naïve individuals, as in [Kuran \(1989\)](#), avoids unrealistic jumps from no to full participation.

⁶ The proof is deferred to [Appendix A.1](#).

The large (small) initial protest size in connection with the strong network benefit gradually increases (decreases) the critical type threshold $\hat{\theta}_i$, eventually leading to the extreme outcome.

This interplay between initial protest size and network effects may very well illustrate the workings of focal points. Focal points, when combined with strong network effects, can spur mass mobilization by attracting a sufficiently large number of initial protesters.

2.3. Model implications and hypotheses

Our theoretical model posits that individuals decide to participate in protests based on a utility function that includes both private (a) and social components (v). While the model does not yield directly testable implications, it provides a structure for identifying key mechanisms. We empirically test whether these mechanisms, standalone and network benefits, are significant predictors of participation. The following hypotheses guide our empirical analysis.

The first two hypotheses are direct premises of the model and address the cornerstone of our framework: the choice of a single network good can represent an individual's rationale for participating in a protest.

Hypothesis 1a. The standalone benefit, as modeled in the utility function, increases an individual's protest participation.

Hypothesis 1b. The network benefit, as modeled in the utility function, increases an individual's protest participation.

Turning to the implications of the model, the relationship between standalone and network benefits determines the equilibrium protest size. Under the assumption that participation costs are similar across different protests, strong network effects lead to extreme outcomes – that is, either small or large protests – whereas weak network effects lead to medium-sized protests.

Consistent with these insights, we expect substantial heterogeneity across societal subgroups in the effect sizes and relative importance of the standalone and network benefits. To test this, we formulate Hypothesis 2, which implies differences in the model's key parameters across different political and protest clusters. The second empirical challenge is thus to appropriately cluster individuals into more homogeneous groups and explore heterogeneities in the drivers of their protest participation.

Hypothesis 2. The relative strength of standalone and network benefits differs across political and protest clusters.

Potential heterogeneity implies that individuals' motivation for joining protests, and thus the relationship between standalone and network benefits, is protest-dependent. For instance, protests related to racial issues may have a different composition of standalone and network benefits than those related to healthcare policies. By identifying and comparing standalone with network benefits across different protests, this approach enables us to identify underlying strong or weak network effects.

3. Empirical strategy

Turning to the empirical strategy, our primary objective is to statistically identify both direct and indirect effects in the context of contemporary protest behavior in the US. We do not aim to estimate the structural model parameters a and v directly. Instead, we employ a spatial autoregressive (SAR) model that enables us to disentangle direct (individual-specific) and indirect (network-based) effects on personal protest decisions. Specifically, we regress the individual protest indicator on a set of covariates and a network component. This approach allows us to decompose the total effect of each variable into a direct effect at the individual level and an indirect effect operating through the social network. While this estimation strategy does not yield structural estimates of a and v , it provides an empirical approximation of their influence. Comparing the magnitudes of direct and indirect effects enables us to assess the relative importance of individual-level versus network-level determinants of protest behavior.

After estimating the spatial autoregressive model on the full ANES sample, we proceed to assess standalone and network effects within more homogeneous subgroups. To this end, we implement two clustering strategies. First, we construct political clusters comprising three groups: left-wing, moderate, and right-wing individuals. Second, we form issue-specific protest clusters corresponding to BLM, immigration, environmental, and healthcare-related protests. Analyzing these subgroups separately allows us to compare the composition of standalone and network effects and to relate our findings to actual protest participation levels observed in 2020, when the survey was conducted. Details on the clustering algorithm are provided in the Appendix.

3.1. Data

The ANES 2020 survey wave fulfills the crucial requirements for the selected empirical identification strategy. First, the database provides information on a representative sample from the US with extensive socio-demographic background information. More than 6000 individuals⁷ participated in the 2020 survey wave, which is a sufficiently large sample for investigating social networks based on individual characteristics. Most importantly, the database provides us with a combination of information on (1) protest behavior, (2) socio-demographic characteristics, (3) associational memberships, and (4) political attitudes. Having this information in a representative sample of the US allows us to build an empirical model for individual protest decisions.

The empirical strategy relies on four categories of data included in the ANES database. Table 1 presents an overview of the variables used and their summary statistics. The binary protest variable indicates whether an individual respondent protested at least once during the past year. This binary protest variable serves as the dependent variable throughout this paper. Socio-demographic characteristics, personal attitudes, and associational memberships are used as control variables and to calculate statistical proximity (network ties) between survey participants. The details of this procedure are explained below. The political attitudes category contains *thermometer* scores in which participants rate their feelings towards several societal groups (the higher the score, the friendlier the

⁷ After dropping observations with missing values.

Table 1

Summary Statistics. The data source is the American National Election Study Wave 2020; the list contains all variables employed in the empirical analysis. Longitude and latitude of respondents' locations are summarized at the state level. All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Protest Variable							
Protest	6100	0.10	0.30	0.00	0.00	0.00	1.00
Socio-Demographic Characteristics							
Age (years)	6100	50.95	17.05	18.00	36.00	65.00	80.00
Education	6100	4.63	2.03	1.00	3.00	6.00	8.00
Income	6100	11.96	6.71	1.00	6.00	18.00	22.00
Black (= 1)	6100	0.087	0.28	0.00	0.00	0.00	1.00
Male (= 1)	6100	0.47	0.50	0.00	0.00	1.00	1.00
Health Status	6100	2.40	1.02	0.00	2.00	3.00	4.00
Married (= 1)	6100	0.53	0.50	0.00	0.00	1.00	1.00
Number of Children	6100	0.62	1.04	0.00	0.00	1.00	4.00
Personal Attitudes							
Left-right-scale	6100	5.56	2.77	0.00	4.00	8.00	10.00
Deviation Left-right-scale	6100	2.22	1.74	0.00	1.00	4.00	5.00
Importance Religion	6100	2.88	1.50	1.00	1.00	4.00	5.00
Trust in others	6100	2.21	0.90	0.00	2.00	3.00	4.00
Longitude	6100	-91.62	15.65	-157.49	-97.33	-79.68	-69.76
Latitude	6100	37.79	5.01	21.11	34.61	41.31	61.41
Associational Participation							
Volunteering	6100	0.30	0.46	0.00	0.00	1.00	1.00
Community Participation	6100	0.19	0.39	0.00	0.00	0.00	1.00
Church Attendance	6100	0.47	0.50	0.00	0.00	1.00	1.00
Political Attitudes Towards...							
Labor Unions	6100	58.74	24.09	0	50	75	100
Conservatives	6100	53.54	27.74	0	40	70	100
Liberals	6100	51.03	29.28	0	30	70	100
Feminists	6100	59.40	26.84	0	50	85	100
Christian Fundamentalists	6100	45.74	28.94	0	25	60	100
Police	6100	70.05	25.38	0	60	85	100
Black Lives Matter	6100	54.02	35.50	0	15	85	100

attitude). Some examples are attitudes towards conservatives, liberals, BLM protesters, and feminists. These attitudes form the basis for analyzing political clusters separately and comparing their respective standalone and network benefits.

To address potential concerns regarding the time frame of the primary analysis, we re-estimate the model using data from 2016 as a robustness check. Since survey respondents were asked between November 8, 2020, and January 4, 2021, whether they had participated in a protest within the past 12 months, all had the opportunity to protest during the summer, when COVID-19 restrictions were generally relaxed. However, while protest activity was legally permissible during the summer of 2020, some individuals may have remained hesitant to participate. To ensure that our findings are not driven by pandemic-related constraints, we replicate the baseline analysis for 2016. The model specification remains unchanged, with the exception of the religious importance variable, which is measured on a five-point scale in 2020 and as a binary indicator in 2016.

3.2. Identification strategy

The empirical model is designed to separate standalone and network benefits in protest participation to assess Hypotheses 1a and 1b. To identify the standalone benefit – meaning the *utility* an individual receives from protesting, excluding any social network elements – we rely on *direct effects* of a set of predictor variables. Specifically, we assess the utility an individual receives merely because of protesting and expressing themselves without any social interaction before, during, or after the protest event. There is a variety of potential standalone protest determinants. To proxy individuals' intrinsic motivation to protest, we include their ideological distance from the political center on a left-right scale. The underlying hypothesis is that individuals with more extreme political views, i.e., those farther from the center, are ideologically more involved in the underlying protest objective and thus experience a larger intrinsic benefit (Marinthe et al., 2025).⁸

Expressive benefits are proxied by education, and psychological benefits by trust in others and religiosity. It is commonly argued that more educated individuals are more likely to be politically active and engage in protest behavior (Olcese et al., 2014; Dahlum and Wig, 2019). Trust in others is expected to positively affect protest participation, as Benson and Rochon (2004) argue that it may induce optimistic estimates of the uncertain components of the individual's utility from participation. That is, all other things being equal, a more trusting individual will expect a lower cost and higher benefit from protest participation.

⁸ It is also plausible that moderates are more likely to protest (Michaeli and Spiro, 2025). In this case, we would expect more extreme values on the left-right scale to have a negative effect on protesting likelihood.

To include additional variation that is not fully proxied through this set of variables, we control for general socio-demographic variables like sex, age, race, income, health status, marital status, and number of children. We expect younger individuals to have a higher intrinsic motivation to protest, as it has been argued that they are typically less constrained by family- or career-related obligations – thus giving them more time to protest – and that they are more prone to taking risks associated with protest participation than older individuals (Wiltfang and McAdam, 1991; Schussman and Soule, 2005). Being married and having children is expected to negatively affect protest participation, as these attributes come with obligations constraining an individual's time and risk-taking capabilities, a mechanism referred to by McAdam (1986) as 'biographical availability'. The effect of income on protest participation is theoretically ambiguous. Similar to the previous point, individuals with higher income may be more constrained by their career and may have more to lose from engaging in risk-taking behavior. Also, individuals with higher income may be more satisfied with the status quo and thus less intrinsically motivated to promote a policy change. On the other hand, higher income may proxy resources that enhance individuals' organizational capacity in accordance with the resource model of political participation (Brady et al., 1995). To account for associational memberships as contributing to individual protest participation, we include volunteering behavior, participation in community meetings, and church attendance. We expect associational memberships to be positively related to protest participation, as it can be argued that such civic participation reflects certain ideals or a sense of duty, which may also give rise to an intrinsic motivation to protest. In sum, these are the covariates of the model for predicting individual participation and, importantly, their direct effects exclude any network-related utility as this is controlled for using the spatial term. Note that we control for a wide range of variables that may proxy individual propensity to protest. If there were spatially correlated omitted variables affecting the likelihood of protesting, then their effect would be falsely attributed to the network effect. This concern is mitigated by our inclusion of control variables as specified above.

The identification strategy for the network benefit relies on a spatial autoregressive model. As discussed, for example, by Souza (2024), a spatial model is appropriate to identify network effects among individuals. That is, if individual A is a close friend of individual B, then A's decision to protest should influence B's decision and vice versa. The spillover is not limited to positive reinforcement. A's decision not to protest should consequently make individual B less likely to join the protest. Such spillover effects are identifiable via spatial regressions (Souza, 2024).⁹ Thus, including a spatial term in a regression analysis in combination with suitable individual-level covariates allows for the identification of the effects explored in the protest decision model from Section 2.

The estimated spatial autoregressive parameter captures the degree of network-based interdependence in protest participation. While this spatial autoregressive parameter itself is not directly interpretable, it reflects the equilibrium relationship among individuals in the network (LeSage, 2015). Therefore, we disaggregate the total effect of the covariates into direct and indirect effects. The direct effect of an increase in, for example, income is how much more likely the individual is to protest when the income increases by one unit, excluding feedback effects of the network. Once the individual is more likely to protest as a consequence of the income shock, their peers are also more likely to protest, and thus they have a second-order effect on the previously shocked individual. These higher-order effects are captured by the indirect effect, which we estimate for all covariates. In the SARAR (spatial autoregressive model with autoregressive disturbances) setting, where the dependent variable and disturbances are spatially lagged, the ratio of direct to indirect effects is the same for all covariates.¹⁰ The ratio provides the crucial insight into how much an individual is affected by changing standalone benefits (direct effect) and how much by network benefits (indirect effects). In sum, the spatial autoregressive model allows for the disaggregation of the standalone and network benefits and, thereby, allows us to approximate the relative magnitudes of the parameters of the proposed model.

The first step in building spatial models is to grasp the social network structure within the sample. For this, we construct a quantitative measure of social proximity between individuals. We rely on the concept of homophily – meaning that individuals who share similarities are more attracted to and exposed to each other and, therefore, are more likely to build friendships and partnerships (McPherson et al., 2001). The first empirical challenge is thus to measure how similar each individual is to all other individuals in the sample. We rely on the inverse of the Mahalanobis distance, which measures how different two individuals are based on a set of variables. The variables used to construct the Mahalanobis distance include: a ten-item left-right political attitude scale, importance of religion, trust in others, age, education, income, volunteering behavior, community participation, church attendance, and the geographic coordinates (longitude and latitude) of the respondent's state of residence. Unlike the Euclidean distance, the Mahalanobis distance accounts for the variables' covariances and hence does not weight highly correlated variables too strongly (Grimm and Yarnold, 2000). All variables are standardized prior to distance calculation.

Given the sample size, we rely on statistical distances between individuals in our sample to construct a synthetic network for the entire dataset. A database containing just over 6000 individuals across the US is, unsurprisingly, too small to identify actual social networks within the population. A solution is to rely on statistical distances among individuals. The distance between individuals A and B thus does not indicate how likely it is that both have a real network tie – e.g., a friendship – but rather indicates that individual A has individuals in their network that are similar to B. On this account, each individual within the sample has a synthetic network based on the whole ANES sample. This approach allows us to investigate whether an individual's synthetic network affects the individual's protest decision.

Eq. (15) presents the regression model, including covariates, a spatial term, regional fixed effects, and an error term. The dependent variable P_i is a binary variable equal to 1 if individual i participated in at least one protest event during the past 12 months and

⁹ Throughout this section, we refer to the estimated spillover effects or peer effects, which are transmitted via a synthetic network as "network effects". Thus, we keep the terminology consistent with the theoretical model.

¹⁰ The size of the direct and indirect effects is determined by the weighting matrix, β coefficients, and the spatial autoregressive parameter.

zero otherwise.¹¹ The matrix X_i includes control variables for sex, marital status, children, age, race, income, education, health, extremism, importance of religion, trust in others, volunteering behavior, community participation, and church attendance. Details about these variables are available in Table 6. Spatial autocorrelation is assessed using the spatial term $W_{invdist} P_{-i}$. The first element is a spatial weighting matrix indicating the inverse distances between each individual i and all other individuals $-i$, and the second element denotes the other individuals' protest decisions P_{-i} . Because individuals are unlikely to be influenced by their whole network, we restrict spillover effects to their fifteen closest neighbors.¹² $\delta_{r(i)}$ denotes a fixed effect for the census region of the individual's state (Northeast, South, Midwest, or West) and ϵ_i is the spatially correlated error term as depicted in Eq. (16).

$$P_i = \alpha X_i + \lambda W_{invdist} P_{-i} + \delta_{r(i)} + \epsilon_i \quad (15)$$

$$\epsilon_i = \rho W_{invdist} \epsilon_i + u_i \quad (16)$$

Simple OLS estimation of the model equation above would lead to biased estimates due to the simultaneity between the dependent variable from individual i and all other individuals $-i$. Therefore, we rely on the GS2SLS estimator proposed by Drukker et al. (2013). This estimator is based on spatial models derived earlier by Kelejian and Prucha (1998, 1999, 2010). The estimators instrument the simultaneous spatially lagged dependent variable with the remaining exogenous variables of each individual. Thereby, they allow for consistent estimation of spatial autoregressive models. To account for spatially correlated errors, we extend the SAR model to a SARAR specification, which explicitly allows for error terms to be correlated across the network. This ensures that our estimates remain robust in the presence of network-based error dependence.

Our regression framework provides the basis for estimating both the direct and indirect effects of each explanatory variable, which are central to our identification strategy for separating standalone and network benefits. Specifically, we interpret a one-unit increase in the variable of interest as leading to a predicted increase in the outcome variable, which can be decomposed into two components: a direct, individual-level effect and an indirect, network-related effect. The direct effect captures the immediate impact on the individual, while the indirect effect reflects the cumulative influence transmitted through the network, where the initial change affects peers, who in turn influence the original individual, generating recursive spillovers. When network interactions are reinforcing, this feedback amplifies the initial impact. Accordingly, we interpret the direct effect as an indication of the standalone benefit and the indirect effect as the network benefit. Importantly, effects are driven by the same underlying variation in the explanatory variable x .

Eqs. (17) to (19) define the direct, total, and indirect effects following LeSage (2015). These effects are derived from the spatial regression model and estimated to interpret the influence of explanatory variables in the presence of spatial dependence. Specifically, the direct effect, $\overline{M}(r)_{direct}$, captures the average impact of a change in a covariate on the outcome without taking the network into consideration. The total effect, $\overline{M}(r)_{total}$, measures the average overall impact of a change in a covariate for one individual on the outcome variable across all individuals in the network. The indirect effect, $\overline{M}(r)_{indirect}$, is then obtained as the difference between the total and direct effects and reflects the average spillover effect, i.e., how a change in one individual's covariate affects others in the network through spatial or social connections.

These effects are computed using the matrix $S_r(W) = (I_n - \lambda W)^{-1} I_n \alpha_r$, where I_n is the identity matrix of size n , λ is the spatial autoregressive parameter, W is the spatial weighting matrix, and α_r is the coefficient of the r -th covariate. The term $(I_n - \lambda W)^{-1}$ captures the spatial multiplier effect, indicating spillover effects throughout the network. The trace (tr) operator in the direct effect formula averages the diagonal elements of the impact matrix, while the total effect is computed as the average of all elements (I_n being an $n \times 1$ vector of ones). The spatial regression, the decomposition into direct and indirect effects, and the associated test statistics are estimated using the `spatialreg` R package provided by Bivand et al. (2021).

$$\overline{M}(r)_{direct} = n^{-1} \text{tr}(S_r(W)) \quad (17)$$

$$\overline{M}(r)_{total} = n^{-1} I_n' S_r(W) I_n \quad (18)$$

$$\overline{M}(r)_{indirect} = \overline{M}(r)_{total} - \overline{M}(r)_{direct} \quad (19)$$

where

$$S_r(W) = (I_n - \lambda W)^{-1} I_n \alpha_r \quad (20)$$

3.3. Heterogeneity analysis

After having obtained average results across a representative sample of the US population, we are interested in exploring heterogeneities among different societal groups across the US. Considering the model dynamics, these differences in the composition of benefits directly translate into different equilibrium outcomes for protests. The key objective of forming groups across the US population is thus to explore potential differences in the causes of their protest participation. To do so, we build clusters and assess

¹¹ Protest events are understood as street protests such as protest marches, rallies, and demonstrations, as per the wording of the question on which this variable is based (see Table 6). Other forms of voicing discontent are not covered by this variable. We cannot differentiate between non-violent and violent protests in this study even though we acknowledge that they may differ in their determinants (Chenoweth and Stephan, 2011; Gomez-Ruiz et al., 2025).

¹² In the weighting matrix, the fifteen nearest neighbors are assigned a value of 1, while all others are set to 0. Then the weighting matrix is row normalized, a standard procedure in estimating spatial models (LeSage, 2015). The number of fifteen closest neighbors is varied in a sensitivity analysis to demonstrate the robustness of the results.

the standalone and network benefits for them separately. There are two subsets we investigate. First, different individuals are clustered into political groups, and we examine whether the protest participation determinants (i.e., standalone and network benefits) vary across these political groups. Second, individuals are clustered based on their likelihood of participating in different protest movements, and then we assess whether the protest determinants vary across these clusters. Both specifications contribute to testing Hypothesis 2, as they explore heterogeneities among protest determinants that help explain differences in protest sizes across movements.

I. Political Clusters

The first heterogeneity analysis consists of differentiating protests according to their *political directions*. We aim to elicit differences between political groups in terms of the underlying reasons for their protest decisions – i.e., are there substantial differences in the standalone and network benefits across different political clusters? To construct political clusters, we rely on a clustering algorithm by Kaufman and Rousseeuw (2009). This algorithm is based on several protest-sensitive political attitudes and forms clusters according to similarity between individuals. We use this algorithm to minimize subjective assumptions in the clustering process. A thorough description of the clustering methodology is available in Section A.2 in the Appendix.

Our approach relies on survey respondents' attitudes towards a set of stylized groups of people within US society. The groups are listed in Table 1 under "Political Attitudes Towards...". These variables are scores from 0 (very low opinion) to 100 (very high opinion) for the following groups: labor unions, conservatives, liberals, feminists, Christian fundamentalists, police, and BLM participants. Clustering individuals according to their attitudes towards these groups should result in groups that share concerns about similar political issues and hold relatively similar political views. For example, individuals with a very low opinion of feminists and a high opinion of conservatives and Christian fundamentalists are more likely to attend the same protest movements. The same applies to individuals with opposing views, who are likely to participate in different types of protest events.

II. Protest Clusters

The final empirical specification explores further heterogeneities by disaggregating the analysis to specific *protest movements*. An in-depth description of the methodology followed is presented in Section A.2 in the Appendix. This approach is intended to shed further light on Hypothesis 2, which claims that there are dominant network effects in (at least some) protest movements. To further identify the conditions under which network effects are most pronounced, we construct clusters of individuals based on the protest causes they support. This allows us to examine how the relative importance of the network and standalone benefits varies across these groups.

The survey includes a question asking respondents to identify what they consider the most pressing problems facing the US. Participants were allowed to name multiple issues. Based on the frequency of responses, we focus on four topics that emerged most prominently: healthcare (42.7%), race relations (19.3%), the environment (6.6%), and immigration (4.3%). These categories serve as the basis for forming issue-specific protest clusters, which allow us to analyze protest behavior in a more targeted way. Importantly, individuals may belong to multiple groups, as participation in one protest does not preclude involvement in another. Therefore, the clusters in this specification are not mutually exclusive.

4. Results

In the following section, the theory-deduced hypotheses are tested by relying on the presented empirical identification strategy. As a first step, Hypotheses 1a and 1b are tested for all individuals across the US sample. The hypotheses indicate that standalone and network benefits shape individual protest participation. Sections 4.2 and 4.3 explore heterogeneities among different societal groups regarding the benefit composition. Thereby, these specifications shed light on Hypothesis 2, which indicates that, given the stark contrast of aggregate protest outcomes, we expect substantially different benefit compositions between different protest movements.

4.1. Baseline estimation

The baseline estimation follows the identification strategy described in Section 3.2, where a spatial weighting matrix is defined via which each individual is affected by their peers. To demonstrate robustness to methodological choices, we present the results for different specifications in which spillovers are given by the 10, 15, or 20 nearest neighbors. Furthermore, we include a set of covariates commonly applied in the literature to estimate their effects on an individual's likelihood to participate in protests. The model is estimated using the presented GS2SLS estimator.

Table 2 presents the spatial regression output for the baseline regression, indicating the presence of robust network effects and the significance of the included covariates. Importantly, the regression coefficients are not yet interpretable because a shock to a particular individual has an impact on the spatial (network) equilibrium, which in turn has feedback effects (LeSage, 2015). We can merely state that some of the covariates, like age, marital status, or the number of children, are likely to affect individual protest participation. As we observe a statistically significant λ and ρ , we conclude that there is indeed substantial spatial (network) dependence within the analyzed sample. Hence, OLS estimation of the same model is biased and inconsistent, while the SARAR specification effectively accounts for spillover effects across the network.

A possible concern for our interpretation of the significant spillover effects is that they may be the result of joint shocks. That is, individuals who are similar to one another according to our distance measure might be simultaneously exposed to a common shock affecting their likelihood to protest. Such a shock could be a reduction in the cost of protesting or a policy making a sub-group of our sample more likely to protest. While we cannot completely rule out this concern, it is mitigated to an extent by also including the variables that compose the Mahalanobis distance measure as control variables. Moreover, we later repeat the analysis for more

Table 2
Baseline spatial regression results.

	Model (1) Neighbors: 10	Model (2) Neighbors: 15	Model (3) Neighbors: 20
Intercept	0.216*** (0.047)	0.179*** (0.043)	0.148*** (0.039)
Male (= 1)	−0.002 (0.007)	−0.002 (0.007)	−0.002 (0.007)
Age (years)	−0.005*** (0.001)	−0.004*** (0.001)	−0.003*** (0.001)
Age (years) ²	0.000** (0.000)	0.000* (0.000)	0.000* (0.000)
Black (= 1)	0.016 (0.014)	0.017 (0.014)	0.017 (0.013)
Income	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)
Education	0.003* (0.002)	0.002 (0.001)	0.000 (0.001)
Left-right-scale	−0.015*** (0.002)	−0.012*** (0.002)	−0.010*** (0.002)
Deviation Left-right-scale	0.023*** (0.003)	0.021*** (0.003)	0.018*** (0.002)
Health	0.001 (0.004)	0.000 (0.004)	0.000 (0.004)
Married (= 1)	−0.026*** (0.008)	−0.025*** (0.008)	−0.025*** (0.008)
Number of children	−0.018*** (0.004)	−0.017*** (0.004)	−0.016*** (0.003)
Importance Religion	0.006** (0.003)	0.004* (0.003)	0.002 (0.002)
Trust in others	0.004 (0.003)	0.003 (0.003)	0.002 (0.003)
Volunteering	0.039*** (0.009)	0.029*** (0.008)	0.020*** (0.007)
Community Participation	0.072*** (0.015)	0.050*** (0.015)	0.028** (0.013)
Church Attendance	0.014** (0.007)	0.015** (0.006)	0.016*** (0.005)
North East	−0.010 (0.010)	−0.006 (0.010)	−0.004 (0.009)
Mid West	−0.025*** (0.009)	−0.019** (0.009)	−0.015* (0.008)
South	−0.028*** (0.009)	−0.024*** (0.008)	−0.021*** (0.007)
Spatial Lag Y: λ	0.366*** (0.123)	0.576*** (0.123)	0.778*** (0.112)
Spatial Lag ϵ : ρ	−0.358*** (0.130)	−0.535*** (0.145)	−0.759*** (0.151)
Observations	6100	6100	6100

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: Baseline SARAR regression results are based on Eq. (14). The full ANES sample is used. Columns differ by the number of nearest neighbors used in the spatial weighting matrix (10, 15, and 20, respectively). All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

homogeneous sub-groups of our sample. With the sample being more homogeneous regarding their political views or their most important issues, it becomes more likely that a common shock affects all individuals in the sample and not just some subset.

Once we obtain the spatial regression output, we estimate the direct, indirect, and total effects of each covariate based on the spatial parameter λ , the weighting matrix W , and the variable's spatial point estimate α . The results of this estimation are presented in Table 3. As can be seen in the table, both the direct and the indirect effects are identified at a statistically significant level. A one-unit increase in *Left Right Scale* (equivalent to becoming “more right-wing”) decreases one's likelihood to participate in a protest by 1.5 percentage points directly and by 0.8 percentage points indirectly, amounting to a total effect of 2.3 percentage points. The indirect effect is driven by the individual's effect on the network equilibrium, where the individual is influenced by the network's feedback effects. A more substantial total effect is observed for the deviation from the political center. If *Left Right Deviation* increases by one unit, the individual is, altogether, 3.7 percentage points more likely to join a protest event.

Since protest behavior is typically modeled without accounting for spatial dependencies, we include an OLS regression of Eq. (15), omitting the spatial term. The results are presented in Table 7 in Appendix A.3. As the spatial term is statistically identified previously, the OLS estimates are biased due to the exclusion of spatial spillovers and do not allow for a decomposition of the total effect into

Table 3
Baseline impacts.

Effect	Direct	Indirect	Total
Male (= 1)	−0.002 (0.007)	−0.001 (0.005)	−0.002 (0.012)
Age (years)	−0.005*** (0.001)	−0.003* (0.001)	−0.007*** (0.002)
Age (years) ²	0.000** (0.000)	0.000 (0.000)	0.000** (0.000)
Black (= 1)	0.016 (0.014)	0.009 (0.012)	0.025 (0.024)
Income	0.000 (0.001)	0.000 (0.000)	0.000 (0.001)
Education	0.003 (0.002)	0.002 (0.001)	0.004 (0.003)
Left-right-scale	−0.015*** (0.002)	−0.008** (0.004)	−0.023*** (0.003)
Deviation Left-right-scale	0.023*** (0.003)	0.013** (0.007)	0.037*** (0.006)
Health	0.001 (0.004)	0.000 (0.003)	0.001 (0.006)
Married (= 1)	−0.026*** (0.008)	−0.015 (0.011)	−0.041** (0.017)
Number of Children	−0.018*** (0.004)	−0.010* (0.006)	−0.028*** (0.008)
Importance Religion	0.006** (0.003)	0.004* (0.002)	0.010** (0.004)
Trust in others	0.004 (0.003)	0.002 (0.003)	0.007 (0.006)
Volunteering	0.040*** (0.009)	0.022** (0.010)	0.062*** (0.012)
Community Participation	0.073*** (0.015)	0.041*** (0.016)	0.114*** (0.015)
Church Attendance	0.015** (0.006)	0.008 (0.006)	0.023** (0.011)
North East	−0.010 (0.011)	−0.005 (0.007)	−0.015 (0.017)
Mid West	−0.025*** (0.009)	−0.014* (0.008)	−0.039*** (0.014)
South	−0.029*** (0.009)	−0.016* (0.009)	−0.045*** (0.014)

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Note: Impact estimation of baseline SARAR regression results is based on Eq. (14). The effect ratio is 0.56 (indirect effect/direct effect). The full ANES sample is used. Columns differ by the estimated effect type. Results are obtained for the specification that includes the 10 nearest neighbors in the weighting matrix. All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

direct and indirect components. Nonetheless, the direction of the estimated effects is broadly consistent with the results reported in Table 3. However, the magnitude of several coefficients is substantially affected by the inclusion of the spatial term. For example, the estimated effect of having an additional child in the household is a 1.8 percentage point decrease in the probability of protesting in the OLS specification, which changes to a 2.8 percentage point decrease in the spatial specification (GS2SLS).

Interpreting these results in light of the theory-deduced hypotheses, we find evidence for Hypotheses 1a and 1b as both standalone (direct effects) and network (indirect effects) benefits affect protest participation. In Proposition 1, we distinguish between two equilibria defined by the relative magnitude of standalone (individual-level) and network (network-level) benefits. The results suggest that the individual-level, direct effect is larger than the network-level, indirect effect, as it accounts for a greater share of the total effect. Expressed as a ratio, the estimated indirect effects are approximately 0.56 of the direct effects (ratio given by indirect effect divided by direct effect size). This comparison provides suggestive evidence that, for the full sample, protest behavior exhibits weak network effects, aligning with equilibrium outcome (a) in Proposition 1.

The findings connect to a broader literature by indicating that protests are games of strategic complements. This fact becomes clear when interpreting the consistently positive statistical identification of λ , indicating positive autocorrelation within the network. The paper thus confirms findings from experimental studies about positive network effects in field experiments (Bursztyn et al., 2021), quasi-experimental studies (Enikolopov et al., 2020a), and studies about online networks (Larson et al., 2019; Mundt et al., 2018). The contribution to these existing studies is the novel application of constructing a synthetic network and applying a spatial autoregressive model to estimate network dependence.

Table 4
Political cluster impacts.

Political cluster	Right-wing	Moderates	Left-wing
Neighbors: 10			
Spatial Lag Y: λ	0.683 (0.189)	0.693*** (0.139)	1.106*** (0.164)
Spatial Lag ϵ : ρ	−0.653 (0.179)	−0.831*** (0.187)	−0.900*** (0.177)
Indirect effect/direct effect	2.02	2.11	omitted
Neighbors: 15			
Spatial Lag Y: λ	0.950*** (0.214)	0.736*** (0.169)	1.209*** (0.187)
Spatial Lag ϵ : ρ	−0.900*** (0.227)	−0.882*** (0.237)	−0.900*** (0.226)
Indirect effect/direct effect	16.90	2.64	omitted
Neighbors: 20			
Spatial Lag Y: λ	1.161*** (0.253)	0.733*** (0.189)	1.464*** (0.213)
Spatial Lag ϵ : ρ	−0.900*** (0.305)	−0.900*** (0.278)	−0.900*** (0.238)
Indirect effect/direct effect	omitted	2.64	omitted

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: Political cluster SARAR regression results are based on Eq. (15). Each column corresponds to a distinct political cluster. Covariate coefficients are omitted for brevity.

4.2. Political clusters

In the previous section, we found evidence for Hypotheses 1a and 1b as both the standalone and network benefits were found to increase an individual's protest participation, as predicted by the proposed model. For the full sample, direct effects seem to exceed indirect effects, indicating a situation of weak network effects formulated in case (a) in Proposition 1. This result may change once we collect more fine-grained evidence in more homogeneous groups. To explore such heterogeneities, we apply the same estimation techniques to political clusters built according to the algorithm presented in the Appendix in Section A.2.1. Within these clusters, individuals show much stronger homogeneity as they are sorted according to their political attitudes.

Table 4 presents the estimated spatial coefficients and the ratio of indirect to direct effects in the estimation of the political clusters. The parameter λ should, by definition, be an element between -1 and 1 . As can be seen, for example, for the right-wing specification with 20 neighbors, the point estimate exceeds this range. Considering the standard errors, the 95% confidence interval clearly includes values below 1 , and hence the exceeding value is likely due to statistical imprecision. Therefore, we interpret the parameter nonetheless. However, calculating the indirect to direct effect ratio is no longer informative, as the Leontief Expansion is only applicable when ρ is an element between -1 and 1 .¹³

Table 4 provides consistent evidence of network dependencies. Across all specifications except 10 nearest neighbors for right-wing individuals, the estimated spatial autoregressive parameter (λ) exceeds 0.7 , indicating substantial spillover effects among individuals within political clusters. Drawing on the indirect-direct effect ratios, the evidence points to strong network benefits within the political clusters. Except for the specification with 10 nearest neighbors for right-wing individuals, all other specifications show ratios above 2 , implying that the indirect effect is at least twice as large as the direct effect, excluding specifications where this comparison is not calculated due to $|\rho| > 1$.

Applying this evidence to the proposed model, we argue that *within* political clusters, protest behavior is characterized by strong network effects, as opposed to the weak network effects found in the previous subsection for the entire sample. This leads us to conclude that, in relation to Proposition 1, protests organized within more homogeneous political groups correspond to case (b), strong network effects. The resulting model prediction is that, for these groups, equilibria with either zero or full participation can emerge. Hence, extreme cases of mobilization are predicted to prevail in protests within these groups. To get an idea of whether this is actually the case, we analyze even more homogeneous groups in the following subsection, where we specifically shed light on four protest movements.

4.3. Protest clusters

While political clusters already help investigate network effects in more homogeneous groups of individuals, the objective of this subsection is to assign individuals to protest movement clusters. The advantage of doing so is that we can compare the measured effects to the aggregate protest outcome during 2020 and relate them to the model predictions. To do so, four topics are chosen:

¹³ If $|\rho| < 1$, the series of feedback loops can be simplified: $(I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \dots$ (LeSage, 2015, p. 34). Once $|\rho| \geq 1$, this transformation is no longer possible and, hence, we omit displaying the indirect to direct effect ratio.

Table 5
Protest cluster impacts.

Protest cluster	BLM	Immigration	Health	Environment
Neighbors: 10				
Spatial Lag Y: λ	0.935*** (0.158)	1.145*** (0.292)	0.313 (0.196)	0.011 (0.256)
Spatial Lag ϵ : ρ	−0.900*** (0.205)	−0.900** (0.387)	−0.188 (0.215)	−0.068 (0.300)
Indirect effect/direct effect	12.159	omitted	0.446	0.011
Neighbors: 15				
Spatial Lag Y: λ	0.853*** (0.187)	1.324*** (0.487)	0.553*** (0.178)	0.731*** (0.283)
Spatial Lag ϵ : ρ	−0.900*** (0.258)	−0.900 (0.596)	−0.468** (0.211)	−0.730* (0.378)
Indirect effect/direct effect	5.402	omitted	1.198	2.594
Neighbors: 20				
Spatial Lag Y: λ	1.073*** (0.210)	1.261** (0.581)	0.727*** (0.159)	0.931*** (0.325)
Spatial Lag ϵ : ρ	−0.900*** (0.288)	−0.900 (0.641)	−0.731*** (0.212)	−0.852** (0.422)
Indirect effect/direct effect	omitted	omitted	2.568	2.594
Observations	882	263	2600	401

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: Protest cluster SARAR regression results are based on Eq. (15). Each column corresponds to a distinct protest cluster. Covariate coefficients are omitted for brevity.

BLM, immigration, health, and environment, which have been particularly salient in 2020. The detailed procedure is described in Section A.2.2.

Interpreting the results presented in Table 5, we find robust evidence of strong network effects for protests related to BLM, immigration, health, and the environment—except in the specification using the 10 nearest neighbors, where the effects for health and immigration are not statistically significant. These results are driven by the high values of the λ -parameter for these protest movements, which subsequently lead to high ratios of indirect to direct effects. As a result, we predict the aggregate protest outcome of BLM, immigration, health, and environment to either show very high or very low participation, as described in the case differentiation *strong network effects* in Proposition 1.

While the theoretical insight of protest benefits being composed of standalone and network benefits can be assumed to hold universally, the heterogeneity in their relative magnitudes across political groups and protest movements is likely to be country-specific. This is because the strength of networks and social capital as well as the demographic composition within a certain political movement may differ between countries, leading to different relative magnitudes of standalone and network benefits. Thus, the insights we gain in the analysis of heterogeneities for the case of the US may not be valid for other countries.

When considering the aggregate protest outcomes in Fig. 2, we can interpret them in light of the identified strong network effects. (Anti-)Racism, as a protest topic, was by far the most salient during 2020. From the modeling perspective, individuals managed to coordinate into the high participation equilibrium for this category of protests. By contrast, protests related to environmental and health issues remained sparse and small in scale, suggesting that despite the presence of strong network effects, individuals failed to coordinate and thus remained in a low-participation equilibrium. Finally, immigration-related protests exhibited a moderate level of participation, suggesting that network effects may not have been fully realized.

The connection of the individual-level findings to the aggregate protest outcome should be understood as an illustrative analysis rather than a statistical test, as there are some limitations to this endeavor. There is no measure of the individual participation cost for any of the protests. Partly, these costs are proxied by the covariates, and generally, they may not differ too much, given the democratic right to protest in the US. However, the varying observational units and different participation rates within the different clusters do not constitute a limitation of this analysis. Spillovers are measured in both positive and negative directions, and hence, there can be strong network effects even if only a few individuals protest in the cluster. Also, cluster size should have no impact on the coefficient size; if anything, small clusters may show larger standard errors due to lower statistical power.

As discussed previously, we find strong evidence for the strategic complementarity of protests for BLM, immigration, health, and the environment. Protest mobilization dynamics for these categories can thus be modeled as coordination games in which both the high and low participation equilibria may materialize, similar to De Mesquita (2010). The murder of George Floyd on May 25, 2020, sparked large protests, shifting participation from low to high. In the context of coordination games, this event qualifies as a Focal Point, which makes a certain equilibrium salient and thus leads to coordination. Such mechanisms are first described by Schelling (1960) from a game-theoretical perspective. Other scholars investigate the role of focal points, mostly interpreted as particular days associated with a country's culture and history, in protest coordination (Truex, 2019; Carter and Carter, 2020; Ketchley and Barrie, 2020). For environmental and healthcare-related protests, no sufficiently salient event occurred to trigger large-scale protests.

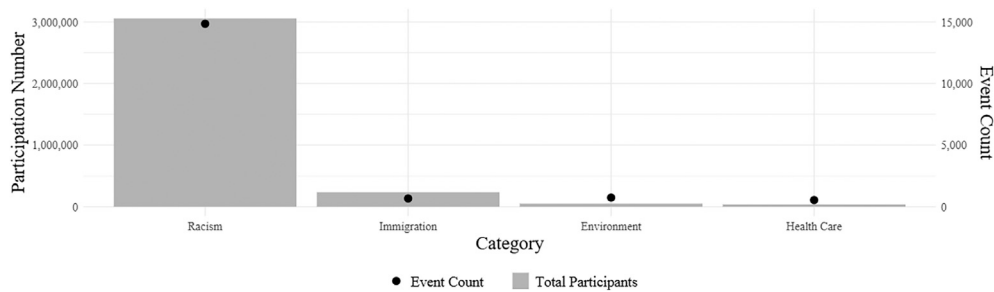


Fig. 2. Illustration of protest size and frequency grouped by protest issues for 2020 according to the Crowd Counting Consortium database.

Another explanation for the large volume of anti-racism protests lies in the interplay between political opportunity structures (POS) and emancipative values. POS theory posits that protest activity becomes more likely when political systems exhibit openness to change (Tarrow, 1996; Kriesi, 1995). In the context of 2020, the anti-racism movement gained momentum following the murder of George Floyd, a pivotal event that may have expanded perceived opportunities for influencing policy. This shift likely facilitated the coordination of anti-racism protests, while mobilization around other issues—such as immigration, environmental protection, and healthcare—remained comparatively limited. More recent research highlights the role of emancipative values in driving protest behavior (Welzel and Deutsch, 2012; Donni et al., 2021). Specifically, Welzel and Deutsch (2012) argue that values centered on freedom and equality precede institutional change and can be activated through protest. Similarly, Donni et al. (2021) find that even when controlling for institutional factors, emancipative values significantly increase the likelihood of protest participation. These cultural foundations offer an additional explanation for the scale and intensity of anti-racism protests relative to other movements.

5. Conclusion

This paper builds on influential models developed by Kuran (1989) and Granovetter (1978) and empirically tests the relevance of the interdependencies in protesting decisions which they propose. First, we apply a model of a single network good by Belleflamme and Peitz (2015) to model individuals' protest decisions. We argue that the individual's protest participation is non-pivotal to the success of the underlying protest objective and that the utility derived from protesting consists of two components: (i) the interaction between an individual's type and the standalone benefit, and (ii) the network benefit, which increases linearly with the expected number of further participants. We then derive equilibrium outcomes where the relation between the standalone benefit and the network benefit determines the aggregate outcome: Under *weak network effects*, a unique equilibrium exists for any exogenous participation cost. Under *strong network effects*, two stable equilibria coexist for intermediate participation costs, namely the extreme outcomes of full and no participation, which illustrates the coordination problem of protests.

The results from the empirical investigation provide evidence on the relative importance of standalone and network benefits as determinants of protest participation. Using a spatial auto-regressive model, we find that both standalone and network benefits are drivers of individual protest participation in the whole US sample. We compare estimated indirect and direct effects of the model's covariates to draw conclusions about whether the protesting decision is characterized by strong or weak network effects. We find evidence for strong network effects in three clusters of individuals with similar political attitudes. Furthermore, our results suggest strong network effects across different protest movements related to race relations, immigration, healthcare, and the environment. Given the observed differences in size and mobilization success of actual protests, this finding suggests heterogeneity in protesters' ability to solve the coordination problem across protest movements.

CRedit authorship contribution statement

Tim Baule: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Jonathan Bothner:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Maximilian Kähny:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

A.1. Mathematical appendix

Proof (Outside Option $\underline{U}$). First, suppose that an individual's outside option ($d = 0$) is type-dependent with

$$\underline{U}_0 = \theta u, \quad (\text{A.21})$$

where θ is uniformly distributed on the interval $[0, 1]$. Then, the critical type threshold denotes

$$\hat{\theta} := \frac{c - v n^e}{a - u}, \quad (\text{A.22})$$

where it is straightforward to see that the type-dependent outside option only affects the level and slope of the function $n(c)$.

Second, suppose that an individual's outside option scales with the expected number of participants, i.e.,

$$\underline{U}_0 = \phi n^e \quad (\text{A.23})$$

with base utility $\phi > 0$. Then, the critical type threshold denotes

$$\hat{\theta} := \frac{c - (v - \phi)n^e}{a}, \quad (\text{A.24})$$

where we can readily see that the scaling outside option, ϕn^e , only affects the steepness of the function $n(c)$.

With the above cases being variable transformations, it is without loss of generality to normalize an individual's outside option to $\underline{U}_0 = 0$. $\square$

Proof (Proof of Proposition 2). Recall the utility function $U_{1,t}(\theta) = \theta a + v n_t^e$, where $n_t^e = n_{t-1}$ and the initial participation level $n_0 \in [0, 1]$. Recall further that with an outside option $\underline{U}_{0,t} = 0$, the critical type threshold at time t denotes $\hat{\theta}_t = (c - v n_{t-1})/a$.

At $t = 1$, the number of participants at a protest denotes

$$n_1(c, n_0) = \begin{cases} 0 & \text{if } n_0 < \frac{c-a}{v}, \\ 1 - \frac{c-vn_0}{a} & \text{if } \frac{c-a}{v} \leq n_0 \leq \frac{c}{v}, \\ 1 & \text{if } n_0 > \frac{c}{v}, \end{cases} \quad (\text{A.25})$$

where we can readily see that $n_1(c, n_0) \geq n_0$ if $n_0 \geq (c-a)/(v-a)$ and that this property holds for any time $t \geq 1$, i.e., $n_t(c, n_0) \geq n_{t-1}(c, n_0)$ if $n_{t-1} \geq (c-a)/(v-a)$.

Lemma 1. For any time $t \geq 1$, the number of participants weakly increases if n_0 is sufficiently large, i.e.,

$$n_t(c, n_0) \geq n_{t-1}(c, n_0) \quad \text{if} \quad n_0 \geq \frac{c-a}{v-a}, \quad (\text{A.26})$$

Considering the corner intervals in (A.25), Lemma 1 implies that if the initial participation satisfies $n_0 \geq c/v$ (if $n_0 < (c-a)/v$), the number of participants remains at the full-participation (no-participation) outcome with $n_t = 1$ ($n_t = 0$) for any time $t \geq 1$.

We can now focus on the interior where $(c-a)/v \leq n_0 \leq c/v$. To solve the first-order linear difference equation, $n_t = 1 - \hat{\theta}_t$, explicitly, we begin by expressing the number of participants at a protest at time $t = 1$ as

$$n_1(c, n_0) = 1 - \frac{c}{a} + n_0 \frac{v}{a}. \quad (\text{A.27})$$

Next, consider the number of protest participants at time $t = 2$. By writing n_2 in terms of n_0 through the substitution of n_1 , we obtain

$$\begin{aligned} n_2(c, n_1) &= 1 - \frac{c - v n_1}{a} \\ \Rightarrow n_2(c, n_0) &= 1 - \frac{c}{a} + \frac{v}{a} \left(1 - \frac{c - v n_0}{a} \right) \\ \Rightarrow n_2(c, n_0) &= \left(1 - \frac{c}{a} \right) \left(1 + \frac{v}{a} \right) + n_0 \left(\frac{v}{a} \right)^2. \end{aligned} \quad (\text{A.28})$$

Analogously, the number of protest participants at time $t = 3$ is given by

$$\begin{aligned} n_3(c, n_2) &= 1 - \frac{c - v n_2}{a} \\ \Rightarrow n_3(c, n_0) &= 1 - \frac{c}{a} + \frac{v}{a} \left[\left(1 - \frac{c}{a} \right) \left(1 + \frac{v}{a} \right) + n_0 \left(\frac{v}{a} \right)^2 \right] \\ \Rightarrow n_3(c, n_0) &= \left(1 - \frac{c}{a} \right) \left(1 + \frac{v}{a} + \left(\frac{v}{a} \right)^2 \right) + n_0 \left(\frac{v}{a} \right)^3 \end{aligned} \quad (\text{A.29})$$

and more generally, for any subsequent time $t = k$, we have

$$\begin{aligned} n_k(c, n_{k-1}) &= 1 - \frac{c - vn_{k-1}}{a} \\ \Rightarrow n_k(c, n_0) &= \left(1 - \frac{c}{a}\right) \left(1 + \frac{v}{a} + \left(\frac{v}{a}\right)^2 + \dots + \left(\frac{v}{a}\right)^{k-1}\right) + n_0 \left(\frac{v}{a}\right)^k. \end{aligned} \quad (\text{A.30})$$

Thus, the number of participants at time $t \geq 1$ can be written as

$$n_t(c, n_0) = n_0 \left(\frac{v}{a}\right)^t + \left(1 - \frac{c}{a}\right) \sum_{i=0}^{t-1} \left(\frac{v}{a}\right)^i, \quad (\text{A.31})$$

and the change in the number of participants per period, for ease of expression, is denoted by $\Delta_t = \left(\frac{v}{a}\right)^{t-1} (n_1 - n_0)$.

- (i) Under weak network effects ($v < a$), Eq. (A.31) constitutes a geometric series in the limit as $t \rightarrow \infty$, converging to its supremum with $\lim_{t \rightarrow \infty} n_t(c, n_0) = (a - c)/(a - v)$.
- (ii) Under strong network effects ($v > a$), the change in the number of participants Δ_t implies that in the limiting case in t , the participation level n_t converges to a no- or full-participation outcome. From Lemma 1, it must follow that $\lim_{t \rightarrow \infty} n_t(c, n_0) = 0$ if $n_0 < (c - a)/(v - a)$ and $\lim_{t \rightarrow \infty} n_t(c, n_0) = 1$ if $n_0 > (c - a)/(v - a)$, which finishes the proof. $\square$

A.2. Identifying political and protest clusters

A.2.1. Identifying political clusters

The individuals are clustered according to the partitioning around medoids (PAM) algorithm by Kaufman and Rousseeuw (2009). The authors developed the K-medoids algorithm, which is more robust to outliers than the more common K-Means algorithm (Kassambara, 2017). A medoid is an observation that is representative of a whole cluster, and all other observations sort themselves around k -medoids. The algorithm determines the choice of medoids; the clustering algorithm works as follows (Kaufman and Rousseeuw, 2009).

1. Randomly select k individuals from the sample. These are the first cluster-medoids.
2. Calculate the Euclidean dissimilarity matrix for all individuals based on the variables “Political Attitudes Towards...” from Table 1.
3. Assign each individual to the cluster-medoid to which it is most similar.
4. Within each cluster, check if there is an alternative medoid that minimizes the average dissimilarity coefficient of the cluster. If this is the case, this alternative medoid is the new cluster-medoid.
5. In case one or more medoids change, return to (3); otherwise, end the algorithm.

Since the ANES database contains more than 6000 individuals, the PAM algorithm is computationally too expensive to estimate. Therefore, we rely on the Clustering Large Applications (CLARA) extension to the k -medoids algorithm, which is also based on Kaufman and Rousseeuw (2009). The CLARA algorithm splits the sample into multiple subsets – 50 in our case. For each subgroup, the k medoids are determined using the PAM algorithm. Thus, we end up with 50 sets of potential medoid combinations. All sets are assessed using the full dataset. The remaining observations are assigned to whichever medoid is closest to them, separately for each set of medoids. Then, the average dissimilarity between the observations and their respective medoid is calculated. The set of medoids that minimizes this number is selected.

Applying the CLARA algorithm based on the seven political attitudes, we identify three clusters as illustrated in Fig. 3. Individuals in cluster 1 have, on average, relatively high opinions about conservatives, the police, and Christian fundamentalists. This cluster thus seems to include individuals who align themselves with conservative ideologies in the US. The average scores for cluster 3 are roughly the opposite. Individuals in cluster 3 have, on average, relatively high opinions about liberals, feminists, BLM protesters, and labor unions. Thus, this cluster seems to include left-leaning individuals. Cluster 2 seems to collect all individuals who do not fit into both political camps. Therefore, this cluster contains individuals who deviate atypically in their opinions from left- or right-leaning individuals or who score each group on the variables equally well. We call this cluster the “moderates”, as their attitudes toward the different groups are less extreme on average.

These cluster interpretations are helpful for assessing heterogeneity in standalone and network benefits. Assigning individuals to different clusters enables separate assessment of these effects. This approach aims to shed light on the drivers of left-wing versus right-wing protests and whether protest motivations differ between left- and right-leaning individuals. We re-estimate the model separately for each of the three clusters, using the same specification as in Eq. (15).

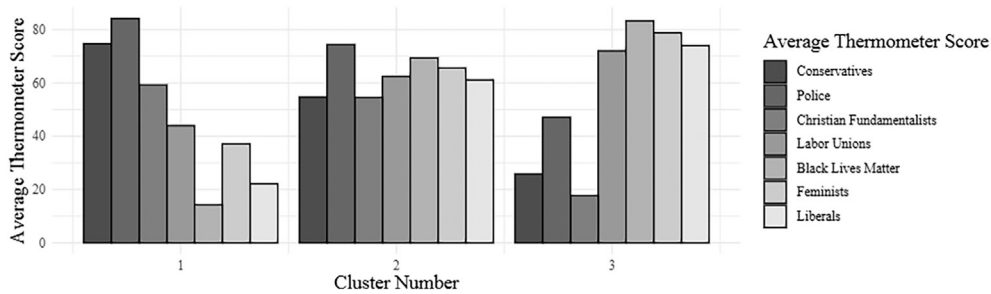


Fig. 3. Average Thermometer Scores for Political Clusters. Cluster 1 includes 2,455 individuals, cluster 2 includes 2,520 individuals, and cluster 3 includes 1,897 individuals.

A.2.2. Identifying protest clusters

The first step in building protest clusters involves assessing participants' awareness of political issues. The survey includes a question that asks participants to identify what they perceive as the most pressing problems facing the US. Respondents could name multiple issues. Based on respondents' answers, we identified four topics that were mentioned most frequently: healthcare (42.7%), race relations (19.3%), environment (6.6%), and immigration (4.3%).

Relying solely on these categories may be problematic because some topics do not directly translate to policy implications. For example, individuals skeptical of BLM protests can name race relations as the biggest problem in the US today, but pro-BLM individuals may also name the same problem. Both groups, however, derive very different policy conclusions from the same issue and are, therefore, very unlikely to join the same protest or to belong to the same protest movement's group of potential protesters. Thus, we combine the naming of the problem with the thermometer scores about political groups. From the group that judges race relations to be one of the most significant problems in the US, only those who indicated a thermometer score of 50 or higher toward the group "BLM protesters" remain in the group. All other individuals are excluded. Thus, this group represents people who see race relations as one of the most pressing issues in the country, while being in line with BLM demands. The individuals are thereby grouped according to their problem awareness and their attitudes toward these protest movements. Based on individuals' survey responses, we thus assign 396 individuals to the group "Environment", 877 individuals to the group "Black Lives Matter", 260 individuals to the group "Immigration", and 2580 individuals to the group "Healthcare". We consider an individual who is a member of one of these groups to be a potential protester for the corresponding issue.

We estimate the model specified in Eq. (15) separately for four subsamples, each corresponding to a distinct protest movement. This second extension enables us to examine whether standalone and network benefits vary across movements. A key advantage of this approach is that individuals may belong to multiple groups, or none at all, depending on their political attitudes. This allows us to define potential protesters with precision and to quantify the magnitude of both standalone and network benefits within this subset. In a subsequent analysis, we relate the ranking of these estimated effects to the observed levels of participation across the four protest movements.

A.3. Variables and robustness appendix

This section provides complementary tables with additional details that were omitted from the main text for brevity. Specifically, Table 6 documents all variables and survey questions from the ANES 2020, Table 7 reports the corresponding OLS estimation results, Table 8 presents the spatial regression results for the political clusters, and Table 9 provides robustness checks for the 2016 baseline specification.

Table 6
Variable description ANES 2020.

Variable	Question
Protest Variable	
Protest	During the past 12 months, have you joined in a protest march, rally, or demonstration, or have you not done this in the past 12 months? ANSWER: 1: yes; 0: no
Socio-Demo. Characteristics	
Age (years)	What is the month, day, and year of your birth? ANSWER: Range 18–80, 80 indicating 80 or older
Education	What is the highest level of school you have completed or the highest degree you have received? ANSWER: 1: Less than high school credential; 2: High school graduate; 3: Some college, no degree; 4: Associate degree - vocational; 5: Associate degree - academic; 6: Bachelor's degree; 7: Master's degree; 8: Professional school/Doctoral degree
Income	Please mark the answer that includes the income of all members of your family during the past 12 months before taxes. ANSWER: Range 1–22, indicating income groups from 0-10k USD to >250k USD
Black (= 1)	What do you consider your main ethnic group or nationality group? <i>Recoded to dummy variable indicating 1 if respondent declares to be Black, non-Hispanic.</i> ANSWER: 1. yes; 0. no
Male (= 1)	What is your sex? 1. Male; 0. Female
Health status	Would you say that in general your health is [excellent, very good, good, fair, or poor/poor, fair, good, very good, or excellent]? ANSWER: 0: poor; 1: fair; 2: good; 3: very good; 4: excellent (recoded)
Married (= 1)	Are you now married, widowed, divorced, separated or never married? <i>Recoded to dummy variable indicating 1 if respondent declares to be married.</i> ANSWER: 1. yes; 0. no.
Number of Children	How many children or teenagers age 0 to 17 live in this household? ANSWER: 0. None; 1: one; 2: two; 3: three; 4: four or more
Personal Attitudes	
Left-right-scale	Where would you place yourself on a scale from 0 to 10 where 0 means the left and 10 means the right? ANSWER: Range 0–10, low values indicating left and high values right.
Deviation Left-right-scale	Absolute number of 5 - answer to left-right-scale question. ANSWER: Range 0–5, where high values indicate extremeness of political attitudes.
Importance Religion	How important is religion in your life? ANSWER: 1: Extremely; 2: Very; 3: Moderately; 4: A little; 5: Not at all
Trust in others	Generally speaking, how often can you trust other people? ANSWER: 0: never; 1: some of the time; 2: about half the time; 3: most of the time; 4: Always
Longitude	Longitude of the respondent's state
Latitude	Latitude of the respondent's state
Associational Participation	
Volunteering	Were you able to devote any time to volunteer work in the past 12 months or did you not do so? ANSWER: 1: yes; 0: no
Community Participation	During the past 12 months, did you attend a meeting about an issue facing your local community or schools? ANSWER: 1: yes; 0: no
Church Attendance	Thinking about your life these days, do you ever attend religious services, apart from occasional weddings, baptisms or funerals? ANSWER: 1: yes; 0: no
Political Attitudes Towards...	
Labor Unions	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Conservatives	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Liberals	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Feminists	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Christian Fundamentalists	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Police	Feelings towards some of [these groups]. <i>Scale 0–100.</i>
Black Lives Matter	Feelings towards some of [these groups]. <i>Scale 0–100.</i>

Note: Variable Description. Questions from the American National Election Survey 2020.

Table 7
OLS estimation results.

	Model (1) Full Sample	Model (2) Right-wing	Model (3) Moderates	Model (4) Left-wing
Male (= 1)	−0.001 (0.007)	0.002 (0.010)	0.002 (0.022)	0.014 (0.009)
Age (years)	−0.006*** (0.002)	−0.004** (0.002)	−0.006 (0.004)	−0.003 (0.002)
Age (years) ²	0.00004*** (0.00001)	0.00003 (0.00002)	0.00001 (0.00004)	0.00002 (0.00002)
Black (= 1)	0.017 (0.014)	0.030* (0.016)	0.022 (0.041)	0.023 (0.035)
Income	−0.0004 (0.001)	−0.001 (0.001)	0.001 (0.002)	−0.0004 (0.001)
Education	0.005** (0.002)	0.002 (0.003)	0.010 (0.006)	−0.001 (0.003)
Left-right-scale	−0.020*** (0.002)	−0.009*** (0.002)	−0.021*** (0.005)	0.002 (0.004)
Deviation Left-right-scale	0.029*** (0.002)	0.008** (0.003)	0.019** (0.007)	0.011*** (0.004)
Health Status	0.001 (0.004)	0.009* (0.005)	−0.001 (0.011)	−0.005 (0.005)
Married (= 1)	−0.027*** (0.008)	−0.014 (0.011)	−0.065** (0.026)	−0.022** (0.011)
Number of Children	−0.018*** (0.004)	−0.007 (0.005)	−0.035*** (0.012)	−0.006 (0.004)
Importance Religion	0.010*** (0.003)	0.010** (0.004)	0.005 (0.009)	0.001 (0.004)
Trust in others	0.006 (0.004)	0.003 (0.005)	0.010 (0.013)	−0.004 (0.006)
Volunteering	0.058*** (0.010)	0.060*** (0.014)	0.084*** (0.026)	0.042*** (0.013)
Community Participation	0.111*** (0.012)	0.067*** (0.017)	0.223*** (0.030)	0.042** (0.017)
Church Attendance	0.013 (0.009)	0.022* (0.012)	0.026 (0.030)	0.011 (0.011)
North East	−0.016 (0.013)	0.003 (0.016)	−0.062* (0.033)	−0.012 (0.017)
Mid West	−0.034*** (0.011)	−0.011 (0.014)	−0.083*** (0.031)	−0.021 (0.014)
South	−0.036*** (0.010)	−0.012 (0.013)	−0.099*** (0.029)	−0.023* (0.013)
Constant	0.290*** (0.044)	0.168*** (0.058)	0.415*** (0.124)	0.119** (0.059)
Observations	6103	2558	1367	2178
R ²	0.128	0.058	0.165	0.033
Adjusted R ²	0.126	0.051	0.153	0.024

Heteroskedasticity robust SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: OLS regression results for the year 2020 as a linear probability model. Model (1) includes the full sample, while Models (2) to (4) differentiate between different political clusters. All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

Table 8
Political cluster spatial regression results.

Cluster	Right-wing	Moderates	Left-wing
Intercept	0.085* (0.051)	0.137 (0.108)	0.074* (0.043)
Male (= 1)	0.002 (0.009)	− 0.001 (0.022)	0.009 (0.008)
Age (years)	− 0.003 (0.002)	0.000 (0.004)	− 0.002 (0.002)
Age (years) ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Black (= 1)	0.027* (0.015)	0.027 (0.038)	0.022 (0.032)
Income	− 0.001 (0.001)	0.002 (0.001)	0.000 (0.001)
Education	0.000 (0.002)	0.004 (0.004)	− 0.002 (0.002)
Left-right-scale	− 0.006*** (0.002)	− 0.009** (0.004)	− 0.001 (0.003)
Deviation Left-right-scale	0.006** (0.003)	0.015*** (0.005)	0.006** (0.003)
Health	0.009** (0.005)	− 0.002 (0.011)	− 0.006 (0.005)
Married (= 1)	− 0.012 (0.011)	− 0.060** (0.024)	− 0.018* (0.010)
Number of children	− 0.007 (0.005)	− 0.032*** (0.011)	− 0.008* (0.004)
Importance Religion	0.006* (0.003)	− 0.001 (0.006)	0.001 (0.002)
Trust in others	0.003 (0.003)	0.008 (0.008)	0.000 (0.004)
Volunteering	0.029*** (0.011)	0.033* (0.019)	0.012 (0.007)
Community Participation	0.026 (0.016)	0.079** (0.034)	0.006 (0.010)
Church Attendance	0.011 (0.008)	0.030* (0.017)	0.000 (0.006)
North East	0.007 (0.012)	− 0.031 (0.023)	− 0.005 (0.011)
Mid West	− 0.005 (0.010)	− 0.055** (0.024)	− 0.009 (0.009)
South	− 0.009 (0.010)	− 0.061*** (0.022)	− 0.016* (0.009)
Spatial Lag Y: λ	0.653*** (0.193)	0.693*** (0.139)	1.102*** (0.163)
Spatial Lag ϵ : ρ	− 0.628*** (0.182)	− 0.831*** (0.187)	− 0.900*** (0.177)

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: Political cluster full SARAR regression results are based on Eq. (15). Each column corresponds to a distinct political cluster. Results are obtained for the specification that includes the 15 nearest neighbors in the weighting matrix. All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

Table 9
Robustness baseline 2016.

	Model (1) Neighbors: 10	Model (2) Neighbors: 15	Model (3) Neighbors: 20
Intercept	0.023 (0.027)	0.032 (0.030)	0.031 (0.030)
Male (= 1)	− 0.003 (0.006)	− 0.002 (0.006)	− 0.003 (0.006)
Age (years)	− 0.001 (0.001)	− 0.001 (0.001)	− 0.001 (0.001)
Age (years) ²	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Black (= 1)	0.021* (0.012)	0.026** (0.013)	0.026** (0.013)
Income	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Education	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Left-right-scale	− 0.003* (0.002)	− 0.004** (0.002)	− 0.004** (0.002)
Deviation Left-right-scale	0.005*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
Health	0.004 (0.003)	0.003 (0.003)	0.003 (0.003)
Married (= 1)	0.002 (0.007)	0.002 (0.007)	0.001 (0.007)
Number of children	− 0.006* (0.003)	− 0.006* (0.003)	− 0.006* (0.003)
Importance Religion	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
Trust in others	0.000 (0.002)	0.000 (0.002)	0.001 (0.002)
Volunteering	− 0.007* (0.004)	− 0.006 (0.004)	− 0.006 (0.004)
Community Participation	0.004 (0.007)	0.004 (0.008)	0.003 (0.009)
Church Attendance	0.007* (0.004)	0.006 (0.004)	0.006 (0.004)
North East	0.006 (0.007)	0.006 (0.007)	0.005 (0.008)
Mid West	0.005 (0.006)	0.005 (0.006)	0.006 (0.006)
South	− 0.002 (0.005)	− 0.003 (0.005)	− 0.003 (0.005)
Spatial Lag Y: λ	1.161*** (0.152)	1.136*** (0.182)	1.186*** (0.198)
Spatial Lag ϵ : ρ	− 0.900*** (0.173)	− 0.900*** (0.231)	− 0.900*** (0.266)
Observations	3257	3257	3257

Heteroskedasticity robust spatial SE in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Note: Robustness for 2016 for the baseline SARAR regression results based on Eq. (14). The full ANES sample is used, with a much smaller sample size for 2016 compared to 2020. Columns differ by the number of nearest neighbors used in the spatial weighting matrix (10, 15, and 20, respectively). All variables, their corresponding survey questions, and the authors' recoding procedures are documented in Table 6.

Data availability

The replication code is available at <https://doi.org/10.7910/DVN/HDQFGL>.

References

- Acemoglu, D., Robinson, J.A., 2001. A theory of political transitions. *Am. Econ. Rev.* 91 (4), 938–963.
- Acemoglu, D., Robinson, J.A., 2005. *Economic Origins of Dictatorship and Democracy*. Cambridge University Press.
- ANES, 2021. ANES 2020 time series study full release [dataset]. www.electionstudies.org.
- Apolte, T., 2012. Why is there no revolution in North Korea? The political economy of revolution revisited. *Public Choice* 150, 561–578.
- BBC, 2018. Yellow vest protests 'economic catastrophe' for France. <https://www.bbc.com/news/world-europe-46499996> (last accessed 5 May 2024).
- Belleflamme, P., Peitz, M., 2015. *Industrial Organization: Markets and Strategies*, second ed. Cambridge University Press edn.
- Benson, M., Rochon, T.R., 2004. Interpersonal trust and the magnitude of protest: a micro and macro level approach. *Comp. Polit. Stud.* 37 (4), 435–457.
- Bivand, R., Mollo, G., Piras, G., 2021. A review of software for spatial econometrics in R. *Mathematics* 9 (11), 1276.
- Brady, H.E., Verba, S., Schlozman, K.L., 1995. Beyond ses: a resource model of political participation. *Am. Polit. Sci. Rev.* 89 (2), 271–294.

- Bursztyn, L., Cantoni, D., Yang, D.Y., Yuchtman, N., Zhang, Y.J., 2021. Persistent political engagement: social interactions and the dynamics of protest movements. *Am. Econ. Rev. Insights* 3 (2), 233–250.
- Cantoni, D., Yang, D.Y., Yuchtman, N., Zhang, Y.J., 2019. Protests as strategic games: experimental evidence from Hong Kong's antiauthoritarian movement. *Q. J. Econ.* 134 (2), 1021–1077.
- Carter, E.B., Carter, B.L., 2020. Focal moments and protests in autocracies: how Pro-Democracy anniversaries shape dissent in China. *J. Confl. Resolut.* 64 (10), 1796–1827.
- Chenoweth, E., Stephan, M.J., 2011. *Why Civil Resistance Works: The Strategic Logic of Nonviolent Conflict*. Columbia University Press.
- Dahlum, S., Wig, T., 2019. Educating demonstrators: education and mass protest in Africa. *J. Confl. Resolut.* 63 (1), 3–30.
- De Mesquita, E.B., 2010. Regime change and revolutionary entrepreneurs. *Am. Polit. Sci. Rev.* 104 (3), 446–466.
- DellaVigna, S., List, J.A., Malmendier, U., Rao, G., 2016. Voting to tell others. *Rev. Econ. Stud.* 84 (1), 143–181.
- Donni, P.L., Marino, M., Welze, C., 2021. How important is culture to understand political protest? *World Dev.* 148, 105661.
- Downs, A., 1957. An economic theory of political action in a democracy. *J. Polit. Econ.* 65 (2), 135–150.
- Drukker, D.M., Egger, P., Prucha, I.R., 2013. On Two-Step estimation of a spatial autoregressive model with autoregressive disturbances and endogenous regressors. *Econ. Rev.* 32 (5–6), 686–733.
- Economides, N., 1996. The economics of networks. *Int. J. Ind. Organ.* 14 (6), 673–699.
- Edwards, B., McCarthy, J.D., Mataic, D.R., 2018. The resource context of social movements. *The Wiley Blackwell companion to social movements* 79–97.
- Egorov, G., Sonin, K., 2024. The political economics of non-democracy. *J. Econ. Lit.* 62 (2), 594–636.
- Ellis, C.J., Fender, J., 2011. Information cascades and revolutionary regime transitions. *Econ. J.* 121 (553), 763–792.
- Enikolopov, R., Makarin, A., Petrova, M., 2020a. Social media and protest participation: evidence from Russia. *Econometrica* 88 (4), 1479–1514.
- Enikolopov, R., Makarin, A., Petrova, M., 2020b. Social image, networks, and protest participation. *Networks, and Protest Participation* (26 April 2020).
- Gerber, A.S., Green, D.P., Larimer, C.W., 2008. Social pressure and voter turnout: evidence from a large-scale field experiment. *Am. Polit. Sci. Rev.* 102 (1), 33–48.
- Gomez-Ruiz, M., Donni, P.L., Marino, M., 2025. Dynamics of protest: understanding violent and nonviolent protest in Africa. *Eur. J. Polit. Econ.* 102745.
- Granovetter, M., 1978. Threshold models of collective behavior. *Am. J. Sociol.* 83 (6), 1420–1443.
- Grimm, L.G., Yarnold, P.R., 2000. *Reading and Understanding MORE Multivariate Statistics*. American Psychological Association.
- Gurr, T.R., 1970. *Why Men Rebel*. Routledge.
- Jenkins, J.C., 1983. Resource mobilization theory and the study of social movements. *Annu. Rev. Sociol.* 9 (1), 527–553.
- Kassambara, A., 2017. *Practical Guide to Cluster Analysis in R: Unsupervised Machine Learning*, vol. 1. Sthda.
- Kaufman, L., Rousseeuw, P.J., 2009. *Finding Groups in Data: An Introduction to Cluster Analysis*. John Wiley & Sons.
- Kelejian, H.H., Prucha, I.R., 1998. A generalized spatial Two-Stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *J. Real Estate Finance Econ.* 17, 99–121.
- Kelejian, H.H., Prucha, I.R., 1999. A generalized moments estimator for the autoregressive parameter in a spatial model. *Int. Econ. Rev.* 40 (2), 509–533.
- Kelejian, H.H., Prucha, I.R., 2010. Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *J. Econom.* 157 (1), 53–67.
- Ketchley, N., Barrie, C., 2020. Fridays of revolution: focal days and mass protest in Egypt and Tunisia. *Polit. Res. Q.* 73 (2), 308–324.
- Kriesi, H., 1995. *New Social Movements in Western Europe: A Comparative Analysis*, vol. 5. U of Minnesota Press.
- Kuran, T., 1989. Sparks and prairie fires: a theory of unanticipated political revolution. *Public Choice* 61 (1), 41–74.
- Larson, J.M., Nagler, J., Ronen, J., Tucker, J.A., 2019. Social networks and protest participation: evidence from 130 million Twitter users. *Am. J. Polit. Sci.* 63 (3), 690–705.
- LeSage, J., 2015. Spatial econometrics. In: *Handbook of Research Methods and Applications in Economic Geography*. Edward Elgar Publishing, pp. 23–40.
- Lohmann, S., 1994. The dynamics of informational cascades: the Monday demonstrations in Leipzig, East Germany, 1989–91. *World Polit.* 47 (1), 42–101.
- Marinthe, G., Kasper, A., Veillé, R., Lalot, F., 2025. Collective Action Among the Extremes? Relations Between Political Ideology, Political Extremism, Emotions, and Collective Action. *Political Psychology*.
- McAdam, D., 1986. Recruitment to high-risk activism: the case of freedom summer. *Am. J. Sociol.* 92 (1), 64–90.
- McCarthy, J.D., Zald, M.N., 1977. Resource mobilization and social movements: a partial theory. *Am. J. Sociol.* 82 (6), 1212–1241.
- McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. *Annu. Rev. Sociol.* 27 (1), 415–444.
- Michaeli, M., Spiro, D., 2025. The dynamics of revolutions. *Eur. J. Polit. Econ.* 102705.
- Mundt, M., Ross, K., Burnett, C.M., 2018. Scaling social movements through social media: the case of black lives matter. *Soc. Media + Soc.* 4 (4), 2056305118807911.
- Olcese, C., Saunders, C., Tzavidis, N., 2014. In the streets with a degree: how political generations, educational attainment and student status affect engagement in protest politics. *Int. Sociol.* 29 (6), 525–545.
- Olson, M., 1971. The logic of collective action: public goods and the theory of groups. In: *Second Printing with a New Preface and Appendix*, vol. 124. Harvard University Press.
- Reuters, 2019. French 'yellow vests' protests cost 0.2 percentage points of growth - Le Maire. <https://www.reuters.com/article/idUSKCN1QH170/> (last accessed 5 May 2024).
- Rohlfis, J., 1974. A theory of interdependent demand for a communications service. *Bell J. Econ. Manag. Sci.* 5 (1), 16–37.
- Schelling, T.C., 1960. *The Strategy of Conflict*, second ed. Harvard University Press, Cambridge, Mass edn.
- Schussman, A., Soule, S.A., 2005. Process and protest: accounting for individual protest participation. *Soc. Forces* 84 (2), 1083–1108.
- Shadmehr, M., 2021. Protest puzzles: Tullock's paradox, Hong Kong experiment, and the strength of weak states. *Q. J. Polit. Sci.* 16 (3), 245–264.
- Souza, P.C., 2024. The empirics of network models. In: *Oxford Research Encyclopedia of Economics and Finance*. Oxford University Press, Oxford.
- Tarrow, S., 1996. States and opportunities: the political structuring of social movements. *Comparative perspectives on social movements: Political opportunities, mobilizing structures, and cultural framings* 90 (2), 41–61.
- Truex, R., 2019. Focal points, dissident calendars, and preemptive repression. *J. Confl. Resolut.* 63 (4), 1032–1052.
- Welzel, C., Deutsch, F., 2012. Emancipative values and non-violent protest: the importance of 'ecological' effects. *Br. J. Polit. Sci.* 42 (2), 465–479.
- Wiedermann, M., Smith, E.K., Heitzig, J., Donges, J.F., 2020. A network-based microfoundation of Granovetter's threshold model for social tipping. *Sci. Rep.* 10, 11202.
- Wiltfang, G., McAdam, D., 1991. Distinguishing cost and risk in sanctuary activism. *Social Forces* 69 (4), 987–1010.
- Zald, M.N., McCarthy, J.D., et al., 1987. *Social Movements in an Organizational Society*. Transaction Books, New Brunswick.