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The Transparency Trap: Quality of Public Information and the Intensity of Revolutionary Violence*

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Abstract

This paper develops a theoretical framework to study how the quality of public information shapes the intensity of revolt in global games of regime change. Building on the canonical literature, I model citizens deciding whether to attack a regime where intensity determines both effectiveness and failure costs. I extend the framework by endogenizing total conflict intensity through the strategic interaction of vanguard groups seeking to maximize the potential of the attack, and including the regime's response. The analysis reveals a non-monotonic "transparency trap": at intermediate beliefs, the relationship between information quality and total violence becomes U-shaped. Intensity is high when information is scarce (serving as a substitute coordination device), minimizes at intermediate levels, and surges again when high transparency facilitates violent coordination. These dynamics persist when intensity is the outcome of decentralized strategic choice. Moreover, as the number of competing vanguard groups increases, so does the equilibrium intensity. I empirically test these predictions drawing 177 events from the Revolutionary Episodes dataset (1900–2014), combined with historical Freedom of Expression indices. The results provide robust support for the U-shaped hypothesis and confirm that higher vanguard competition structurally escalates conflict. These findings highlight that transparency reforms can have counterintuitive effects, providing relevant policy implications.

Key Words: Global Games, Regime Change, Public Information, Revolution, Violence.

JEL Codes: D72, D74, H56, P16.

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"Only by taking infinitesimally small units for observation (the differential of history, that is, the individual tendencies of men) and attaining to the art of integrating them (that is, finding the sum of these infinitesimals) can we hope to arrive at the laws of history."

Lev Tolstoy,
War and Peace

1 Introduction

The outcome of political uprisings often depends less on the depth of public discontent than on whether citizens are able to coordinate and act together. Even when dissatisfaction is widespread, collective action runs into the familiar free-rider problem: many people may want change, but the personal risks and costs, especially when violence is in the picture, can keep them from getting involved unless they believe others will also take part (Olson, 1965). This difficulty is particularly relevant when repression is likely and when information about the regime's strength is uncertain.

Over the past three decades, the global games of regime change framework (Morris and Shin, 1998; Morris and Shin, 2003) has provided a powerful way to study coordination under incomplete information. By introducing small amounts of private noise into agents' information, global games generate a unique equilibrium in settings where standard models yield multiple possible outcomes. While the approach was first applied to currency crises and bank runs (Carlsson and Damme, 1993; Goldstein and Pauzner, 2005), it has since evolved and been adapted to political settings. Angeletos et al. (2007) examine dynamic coordination games in a general framework, but their treatment of belief updating and timing has clear parallels to political mobilization. Other related and relevant models shed light on the role of revolutionary entrepreneurship in regime change settings (Bueno de Mesquita, 2010), and on the role of information manipulation in protest environments (Edmond, 2013).

Across much of this literature, however, intensity of protest and violence mostly appear as external factors, even though history suggests they are often the result of a calculated strategy. Historical experience supports the view that intensity in uprisings is often the product of deliberate strategy by small, organized groups. The Bolshevik seizure of power in October 1917 was not a spontaneous spillover from strikes, but a carefully coordinated armed takeover by disciplined revolutionary cadres (Fitzpatrick, 2017; Pipes, 1990). Similarly, the 1959 Cuban Revolution saw Fidel Castro's July 26 Movement deliberately escalate guerrilla operations at moments when Batista's regime appeared vulnerable (Gott, 2004). In the Iranian Revolution of 1979, underground networks linked to clerical leadership orchestrated targeted attacks to provoke overreactions, aiming to radicalize the opposition (Kurzman, 2004).

These historical examples illustrate that revolutionary violence is rarely incidental; it is often planned to influence expectations and regime's reaction, so to maximize the chances of success. Moreover, these strategic choices are shaped by the internal structure of the opposition. In the literature on civil conflict, scholars have argued that fragmented movements are structurally prone to escalation. Rival groups may engage in "outbidding," using extreme violence to signal commitment and win public support over competitors (Bloom, 2004). While this link between fragmentation, competition, and violence is well documented in civil wars (Bakke et al., 2012; Pearlman, 2011), it remains to be investigated how such dynamics interact with the broader problem of mass coordination in regime change episodes.

A different body of work stresses the role of information in triggering protest. Lohmann (1994) and Lohmann (2000) model demonstrations as informational cascades, while Kuran (1991) explains how small shocks can set off large mobilizations. Real world examples, such as the Tunisian protests of 2010, show how isolated events can shift common beliefs (Anderson, 2011). More recent studies extend this logic to communication technology, arguing that better information lowers coordination costs and facilitates synchronization (Pierskalla and Hollenbach, 2013; Little, 2016). However, the relationship between stability and openness is not always linear; for instance, transitional "anocracies" are often found to be more unstable than fully authoritarian regimes (Hegre et al., 2001). This suggests that the precise effect of information quality on the intensity of revolt deserves deeper theoretical investigation.

The aim of this study is to investigate comprehensively the role of intensity of revolt, looking at how it can enhance the effectiveness of an attack, how it can trigger retaliation, and how it reacts to the quality of public information. This work combines the strands of literature previously cited by embedding intensity into a global game of regime change with both public and private information. The starting point is a benchmark model in which intensity is fixed. The model is then extended to make intensity the outcome of strategic interaction between vanguard groups, each paying the cost of its own contribution but competing toward the same goal. Finally, the regime's response is included to obtain total conflict intensity. This links the global games approach to the literature on costly collective action (Tullock, 1971) and to models of strategic conflict (Fearon, 1995). When analyzing the strategic interaction between vanguard groups, I investigate different possible configurations of interplay, including simultaneous Cournot-like models and sequential Stackelberg interactions.

The theoretical analysis yields two key results regarding the drivers of revolutionary intensity. First, regarding the information environment, I find a non-monotonic pattern: when the public signal strongly favors or disfavors the regime, precision has linear effects, but at intermediate beliefs, the relationship becomes U-shaped. Intensity is high when information is scarce (serving as a substitute coordination device), minimizes at intermediate levels, and surges again when high transparency facilitates violent coordination. Second, I find that equilibrium intensity increases with the number of vanguard groups contributing to the revolt. This confirms that the competitive incentives identified in the civil war literature (Bloom, 2004) play a crucial structural role in mass uprisings as well.

I empirically test these predictions drawing 177 events from the *Revolutionary Episodes* dataset (Beissinger, 2022), which covers 345 mass mobilizations from 1900 to 2014, combined with historical Freedom of Expression indices. The empirical results provide robust support for both theoretical mechanisms. First, I identify a statistically significant generalized U-shaped relationship between information quality and conflict intensity. Second, I find that intensity is strictly increasing in the number of competing vanguard groups, confirming that fragmentation structurally escalates conflict.

These findings are relevant for policy. Besley and Prat (2006) find that freer media can limit political survival by reducing control on public opinion. The results here suggest a more complicated picture: in some situations, more precise public information can lower the appeal of violence, while in others it can make violent coordination easier. Similar tensions appear in the literature on transparency and political stability (Hollyer et al., 2015; Hollyer et al., 2021). Policies such as media liberalization or open-data reforms, often promoted as strengthening governance (Islam, 2006), may in certain contexts raise the risk of high intensity mobilization. The broader point is that the political effects of transparency depend on how information shapes strategic expectations and cannot be assumed to be always stabilizing.

2 Model with Private Information

2.1 Agents, Actions and Payoffs

The population consists of a continuum of citizens indexed by $i \in [0, 1]$, such that the overall mass of the population equals 1.

The fundamental of the game is captured by θ, which can be interpreted as the strength of the status-quo regime. Before the game starts, citizens have an uninformative prior on the distribution of θ, that is $\theta \sim U(\mathbb{R})$.

The citizens' possible actions are:

$$\begin{cases} s_i = 1 & \text{attack} \\ s_i = 0 & \text{not attack.} \end{cases}$$

The citizens' payoffs correspond to

	Successful attack, $P = S \cdot f(v) > \theta$	Unsuccessful attack, $P = S \cdot f(v) \leq \theta$
$s_i = 1$	$1 - c$	$-c - g(v)$
$s_i = 0$	0	0

Table 1: Payoffs by outcome

where

$$S = \int_0^1 s_i di$$

is the mass of citizens attacking, and $c \in [0, 1]$ is the baseline cost of attacking for citizens, it represents the opportunity cost of not abstaining in the uprising against the status quo regime, and is paid regardless of the outcome of the attack. $v \in [0, 1]$ is the intensity of revolt.

P captures the total power of the attack, which depends not only on the mass of citizens revolting, but also on the intensity of the revolt itself. Therefore, I model intensity impacting on the power of the attack through the function $f(v)$. This function captures a multiplication effect of intensity on a given mass of agents involved in the uprising. Therefore, a higher intensity is expected to impact positively on the power of the attack via $f(v)$.

I model intensity of revolt not in levels but rather in fractions, where $v = 1$ would represent the highest possible intensity and $v = 0$ the lowest. Considering both extremes as limit cases, also peaceful protests such as strikes and demonstrations would be modeled with a relatively low, but non-zero, intensity of revolt.

The function $f(v)$ is defined as $f(v) = \varepsilon + h(v)$, where $h(v) : [0, 1] \to [0, 1]$ is a continuous and differentiable function, monotonically increasing in v. Therefore, with a sensible value of $\varepsilon \in [0, 1]$, the following effects would result for a given mass of protesters $S(\theta)$. A very low intensity of revolt would deflate the total power of the attack to $S(\theta) \cdot \varepsilon$. In the opposite direction, the maximum intensity would inflate it to $S(\theta) \cdot (\varepsilon + 1)$.

Moreover, the intensity of revolt can cause an additional cost in case of a failed attack, to those who participated in the uprising. This effect is mediated by the function $g(v) : [0, 1] \to [0, 1]$, continuous and differentiable, and monotonically increasing in v. Interpreting $g(v)$ as the response of the status quo regimes, it is reasonable to assume that agents only incur this cost in the case of a failed attack, with $g(v)$ representing an act of retaliation from the status quo regime on those who tried to overthrow it. In the scenario of a successful uprising, instead, the regime's response, despite being present, does not represent a cost as the revolution is successful and the regime is finally overthrown. The fall of the status quo regime's reward compensates the regime's response cost.

Both effects of intensity of revolt, mediated respectively by $f(v)$ and $g(v)$, can drive the outcome in favor of regime change. However, the mechanisms they work through are different. $f(v)$, strengthening the attack, has an overall favorable effect on regime change. $g(v)$, instead, represents an opportunity cost of not participating in a successful uprising. Consequently, it polarizes the population: it incentivizes those who believe the regime is weak to attack, while simultaneously deterring those who perceive the regime as strong by increasing the penalty for a failure.

As in the standard global games of regime change literature, this model lies in a setting that assumes the existence of some states of the world in which the status quo regime falls regardless of the actions of individuals. Similarly, it is assumed that there exist some states of the world where the regime survives regardless of the actions of individuals.

The region in which the regime always falls, is that where $\theta < 0$. Instead, where $\theta > f(v)$, for a given v, the regime always survives. Notice that this means that if it were commonly known that $\theta < 0$, then all individuals would have a dominant strategy to abandon the regime or rebel. In the same way, if it were commonly known that $\theta > f(v)$, then all individuals would have a dominant strategy to support it.

I recognize that the functional form of $f(v)$ and $g(v)$ can heavily affect the results. I consider this to be a strength of the model, as I believe that the sensitivity to violence or intensity of revolt, and the retaliation technology, are features specific to a given society. Therefore, this structure of the model allows me to design and represent a variety of societies of interest.

I will later in the analysis model the intensity of revolt v as an endogenous variable resulting from a strategic interaction between vanguard groups.

2.2 Information Structure

Each citizen receives a private signal on the fundamental of the game θ, which captures the strength of the status quo regime. The signal is

$$x_i = \theta + \varepsilon_i,$$

where

$$\varepsilon_i \sim N\left(0, \frac{1}{\alpha}\right)$$

is independent and identically distributed across individuals, and independent of θ.

According to their private information, citizens update their beliefs on the fundamental as follows,

$$\theta \mid x_i \sim N\left(x_i, \frac{1}{\alpha}\right).$$

It is a standard approach to assume that citizens act according to a cutoff strategy which is common to all the players:

$$\begin{cases} s_i = 1 & \text{if } x_i < \bar{x} \\ s_i = 0 & \text{if } x_i \geq \bar{x}, \end{cases}$$

where $\bar{x}$ is the participation threshold.

2.3 Solution of the Model

The solution of the model follows Morris and Shin (1998), and Morris and Shin (2003).

From the law of large numbers, it is commonly known that for a given θ and a participation threshold x^*, the mass of agents revolting will be

$$S(\theta) = \Pr(x < x^* \mid \theta) = \Phi\left(\sqrt{\alpha}(x^* - \theta)\right),$$

and the associated power of the attack, for a given v, will be

$$P(s, \theta) = S(\theta) \cdot f(v) = f(v) \cdot \Pr(x < x^* \mid \theta) = f(v) \cdot \Phi\left(\sqrt{\alpha}(x^* - \theta)\right).$$

It follows that to fix an arbitrary participation threshold is equivalent to fix a critical value

$$\theta^* = P(s, \theta^*) = f(v) \cdot S(\theta^*) \Leftrightarrow \theta^* = f(v) \cdot \Phi\left(\sqrt{\alpha}(x^* - \theta^*)\right).$$

Now let us proceed to compute the indifference condition with respect to the marginal agent

$$\begin{aligned} \Pr(P > \theta)(1 - c) + \Pr(P \leq \theta)(-c - g(v)) = \\ = \Pr(\theta < \theta^*)(1 - c) + \Pr(\theta \geq \theta^*)(-c - g(v)) = \\ = 0. \end{aligned}$$

Therefore, it is possible to write

$$\Pr(\theta < \theta^*) = \frac{c + g(v)}{1 + g(v)},$$

and

$$\Pr(\theta < \theta^* \mid x^*) = \Phi(\sqrt{\alpha}(\theta^* - x^*) = \frac{c + g(v)}{1 + g(v)}.$$

Moreover, note that

$$\frac{c + g(v)}{1 + g(v)} < 1,$$

since

$$0 < c < 1.$$

At this point, it follows that the equilibrium pair (x^*, θ^*) is the one that solves the following system

$$\begin{cases} \theta^* = f(v) \cdot \Phi\left(\sqrt{\alpha}(x^* - \theta^*)\right) \quad (1) \\ \Phi(\sqrt{\alpha}(\theta^* - x^*)) = \dfrac{c + g(v)}{1 + g(v)} \quad (2). \end{cases}$$

Performing the computations, from equation (2),

$$x^* = \theta^* - \frac{1}{\sqrt{\alpha}}\Phi^{-1}\left(\frac{c + g(v)}{1 + g(v)}\right),$$

which can be substituted in equation (1).

Solving the system yields

$$\begin{cases} \theta^* = f(v)\dfrac{1 - c}{1 + g(v)} \\ x^* = f(v)\dfrac{1 - c}{1 + g(v)} - \dfrac{1}{\sqrt{\alpha}}\Phi^{-1}\left(\dfrac{c + g(v)}{1 + g(v)}\right). \end{cases}$$

Thus, the following proposition holds.

Proposition 1. *The unique equilibrium in monotone cutoff strategies of the Global Game of Regime Change with private information is given by the couple*

$$\begin{cases} \theta^* = f(v)\dfrac{1 - c}{1 + g(v)} \\ x^* = f(v)\dfrac{1 - c}{1 + g(v)} - \dfrac{1}{\sqrt{\alpha}}\Phi^{-1}\left(\dfrac{c + g(v)}{1 + g(v)}\right). \end{cases}$$

where

$$\begin{cases} s_i = 1 \quad \text{if } x_i < x^* \\ s_i = 0 \quad \text{if } x_i \geq x^*. \end{cases}$$

Note that in this simple game (x^*, θ^*) can be found in explicit form.

It is possible to compute the derivative

$$\frac{\partial x^*}{\partial v} =$$

$$= \frac{-1 + c}{\sqrt{\alpha}(1 + g(v))^2}\left[- \sqrt{\alpha}(1 + g(v))f'(v) + \right.$$

$$\left. + g'(v)\left(\sqrt{\alpha}f(v) + \Phi^{-1\prime}\left(\frac{c + g(v)}{1 + g(v)}\right)\right)\right].$$

Which could be rewritten recalling that

$$\Phi^{-1\prime}(y) = \frac{1}{\phi(\Phi^{-1}(y))}.$$

The sign of this derivative is ambiguous, allowing for the existence of critical points.

Now, it is relevant to visualize an example of the plot of the equilibrium participation threshold. In order to do so, it is necessary to impose a functional form to $f(v)$ and $g(v)$. This means, as previously hinted, to decide which form of society the model will capture.

Specifically, I am interested in a scenario in which the effect of intensity of revolt is not trivial. Meaning, I am interested in a society in which a variation in intensity can both increase and decrease the aggregate participation in an attack. Therefore, I am investigating the case with $h(v) = v^{\frac{1}{3}}$ and $g(v) = v^3$. In this way, I am representing a society in which the effect of intensity of revolt on the strength of the attack is dominant for low values of v. However, the effect of regime's response catches up as v gets closer to 1. This captures a society in which an increase in intensity of revolt can impact positively on the potential of the attack before retaliation kicks in, a specification that fits moderately retaliative ruling regimes.

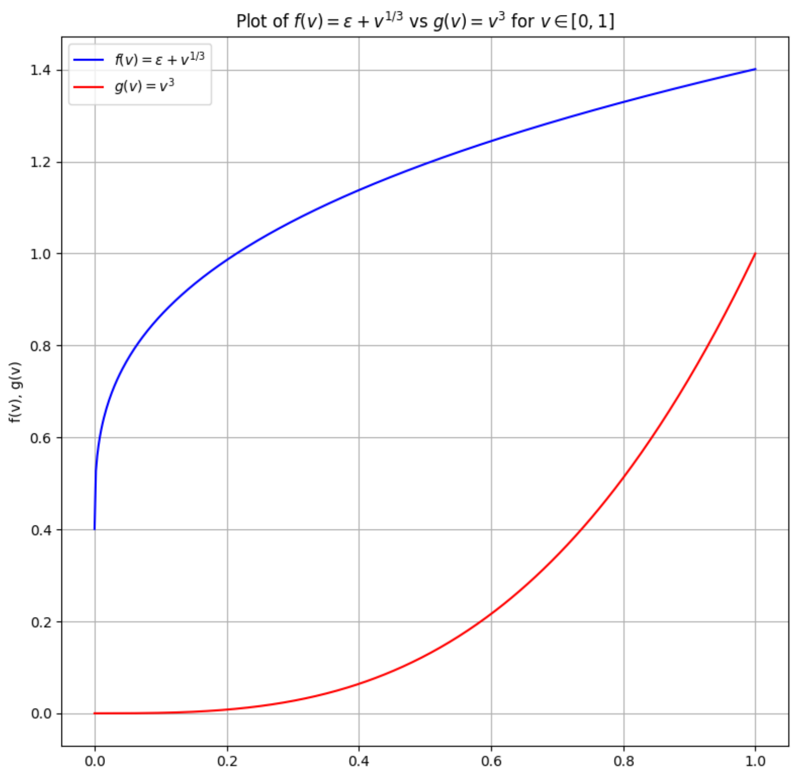

Figure 1: Effect of intensity of revolt on the potential of the attack and on regime's response, with $\varepsilon = c = 0.4$.

Let us now have a visual representation of the participation threshold as function of intensity of revolt, for a set of sensible parameters of interest.

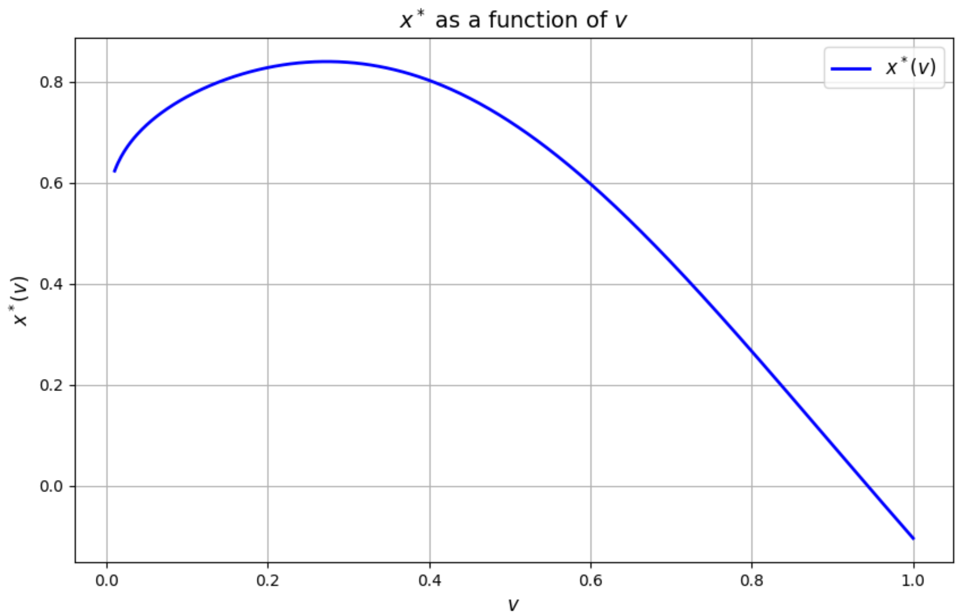

Figure 2: Participation threshold with $c = 0.4$, and $\alpha = 1$.

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Maximum x* value: 0.8398
Corresponding v* value: 0.2729
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It shows that in this framework the curve of x^*, indirectly but unequivocally capturing aggregate participation in an attack, shows a maximum. This means that in this case there exists a unique strictly positive intensity of revolt maximizing the mass of agents participating in an uprising.

3 Model with Public and Private Information

3.1 Agents, Actions and Payoffs

In this version of the model, the fundamental elements of the structure of the game remain unchanged relative to the private information-only benchmark. Specifically, the set of agents, their respective action spaces, and the functional forms of their payoffs are identical to those defined previously. Thus, the extension does not alter the strategic environment but rather modifies the informational structure under which agents interact.

3.2 Information Structure

The fundamental of the game θ is drawn by nature from a normal distribution, that is

$$\theta \sim N\left(z, \frac{1}{\alpha}\right).$$

This is the public component of information about the fundamental of the game, which updates the initial uninformative common prior about θ.

Each citizen then receives a private signal

$$x_i = \theta + \varepsilon_i,$$

where

$$\varepsilon_i \sim N\left(0, \frac{1}{\beta}\right)$$

is independent and identically distributed across individuals, and independent of θ.

In this model, there are both a public and a private component in the information structure. The public component can also be seen as an updated common prior on the fundamental of the game. The information structure is completely defined with (β, α, z), that is, the precision of private information, the precision of public information, and the mean of public information.

Therefore, the citizens update their beliefs about θ by Gaussian updating, conditional on the private signal and on the mean of θ, which is z

$$\theta \mid x_i, z \sim N\left(\frac{\beta x_i + \alpha z}{\alpha + \beta}, \frac{1}{\alpha + \beta}\right).$$

In this framework, players also form beliefs on other players' private signal

$$x_j \mid x_i, z \sim N\left(\frac{\beta x_i + \alpha z}{\alpha + \beta}, \frac{2\alpha + \beta}{2(\alpha + \beta)}\right).$$

It is the standard approach to assume that citizens act according to a cutoff strategy which is common to all the players:

$$\begin{cases} s_i = 1 & \text{if } x_i < \bar{x} \\ s_i = 0 & \text{if } x_i \geq \bar{x}, \end{cases}$$

where $\bar{x}$ is the participation threshold.

3.3 Solution of the Model

The methods employed to achieve a solution of the model are inspired by Morris and Shin (2003) and Angeletos et al. (2007). From the law of large numbers, it is known that for a given θ and a participation threshold x^*, the mass of agents revolting will be

$$S(\theta) = \Pr(x < x^* \mid \theta) = \Phi\left(\sqrt{\beta}(x^* - \theta)\right),$$

and the associated power of the attack, for a given v, will be

$$P(v, \theta) = S(\theta) \cdot f(v) = f(v) \cdot \Pr(x < x^* \mid \theta) = f(v) \cdot \Phi\left(\sqrt{\alpha}(x^* - \theta)\right).$$

It follows that to fix an arbitrary participation threshold is equivalent to fix a critical value

$$\theta^* = P(v, \theta^*) = f(v) \cdot S(\theta^*) \Leftrightarrow \theta^* = f(v) \cdot \Phi\left(\sqrt{\alpha}(x^* - \theta^*)\right).$$

Now let us proceed to compute the indifference condition with respect to the marginal agent

$$\begin{aligned} &\Pr(P > \theta)(1 - c) + \Pr(P \leq \theta)(-c - g(v)) = \\ &= \Pr(\theta < \theta^*)(1 - c) + \Pr(\theta \geq \theta^*)(-c - g(v)) = \\ &= 0. \end{aligned}$$

Therefore, it is possible to write

$$\Pr(\theta < \theta^*) = \frac{c + g(v)}{1 + g(v)}.$$

Moreover, note that

$$\frac{c + g(v)}{1 + g(v)} < 1,$$

Since

$$0 < c < 1.$$

It holds

$$\begin{aligned} \Pr(\theta < \theta^* \mid x^*) &= \left(1 - \Phi\left(\sqrt{\alpha + \beta}\left(\frac{\beta x^* + \alpha z}{\alpha + \beta} - \theta^*\right)\right)\right) = \\ &= \Phi\left(\sqrt{\alpha + \beta}\left(\theta^* - \frac{\beta x^* + \alpha z}{\alpha + \beta}\right)\right) = \frac{c + g(v)}{1 + g(v)}. \end{aligned}$$

Therefore, the equilibrium couple (x^*, θ^*) is identified by the following system

$$\begin{cases} \theta^* = f(v) \cdot \Phi\left(\sqrt{\beta}(x^* - \theta^*)\right) & (1) \\ \Phi\left(\sqrt{\alpha + \beta}\left(\theta^* - \dfrac{\beta x^* + \alpha z}{\alpha + \beta}\right)\right) = \dfrac{c + g(v)}{1 + g(v)} & (2). \end{cases}$$

Performing the computations, from equation (2),

$$x^* = \frac{1}{\beta}\left\{\left[\theta^* - \frac{1}{\sqrt{\alpha + \beta}}\Phi^{-1}\left(\frac{c + g(v)}{1 + g(v)}\right)\right](\alpha + \beta) - \alpha z\right\},$$

which can be substituted in equation (1).

Solving the system it results

$$\begin{cases} x^* = \dfrac{1}{\beta}\left\{\left[\theta^* - \dfrac{1}{\sqrt{\alpha+\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right)\right](\alpha+\beta) - \alpha z\right\} \\ \theta^* = f(v)\cdot\Phi\left(\dfrac{\alpha}{\sqrt{\beta}}\theta^* - \sqrt{\dfrac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right) - \dfrac{\alpha}{\sqrt{\beta}}z\right). \end{cases}$$

Note that in this framework the equilibrium couple is implicitly defined.

Proposition 2. *The equilibrium in monotone cutoff strategies of the Global Game of Regime Change with private and public information is unique if* $\beta \geq \frac{\alpha^2}{2\pi}(1+\varepsilon)^2$.

Proof. The proof is inspired by Angeletos et al. (2007). It is convenient to start from the equation

$$\theta^* = f(v)\cdot\Phi\left(\sqrt{\beta}(x^*-\theta^*)\right).$$

Solving for x^*, it results

$$x^* = \theta^* + \frac{1}{\sqrt{\beta}}\Phi^{-1}\left(\frac{\theta^*}{f(v)}\right).$$

Now, it is possible substitute it in the indifference condition of the marginal agent

$$\begin{cases} x^* = \theta^* + \dfrac{1}{\sqrt{\beta}}\Phi^{-1}\left(\dfrac{\theta^*}{f(v)}\right) \\ 1 - \Phi\left(\sqrt{\alpha+\beta}\left(\dfrac{\beta x^* + \alpha z}{\alpha+\beta} - \theta^*\right)\right) = \dfrac{c+g(v)}{1+g(v)}. \end{cases}$$

It follows that

$$1 - \Phi\left(\frac{\sqrt{\beta}}{\sqrt{\alpha+\beta}}\left(\Phi^{-1}\left(\frac{\theta^*}{f(v)}\right) + \frac{\alpha}{\sqrt{\beta}}(z-\theta^*)\right)\right) - \frac{c+g(v)}{1+g(v)} = 0,$$

which can be rewritten as

$$U(\theta^*, \beta, \alpha, z) = 0,$$

where of course

$$U(\theta, \beta, \alpha, z) =$$
$$= 1 - \Phi\left(\frac{\sqrt{\beta}}{\sqrt{\alpha+\beta}}\left(\Phi^{-1}\left(\frac{\theta}{f(v)}\right) + \frac{\alpha}{\sqrt{\beta}}(z-\theta)\right)\right) - \frac{c+g(v)}{1+g(v)}.$$

$U(\theta, \cdot)$ is continuous and differentiable in $\theta \in (0, f(v))$. Outside of this interval there are the dominance regions, that were previously investigated.

Before proceeding, let us recall that

$$\lim_{x\to 0}\Phi^{-1}(x) = -\infty, \text{ and } \lim_{x\to 1}\Phi^{-1}(x) = +\infty$$

Therefore, for a given v and the corresponding value $f(v)$

$$\lim_{\theta \to 0} U(\theta) = 1 - \frac{c + g(v)}{1 + g(v)},$$

and

$$\lim_{\theta \to f(v)} U(\theta) = -\frac{c + g(v)}{1 + g(v)}.$$

So, since

$$0 < \frac{c + g(v)}{1 + g(v)} < 1,$$

a solution always exists.

Moreover,

$$\frac{\partial U(\theta)}{\partial \theta} =$$

$$= -\frac{\sqrt{\beta}}{\sqrt{\beta + \alpha}} \phi \left(\frac{\sqrt{\beta}}{\sqrt{\beta + \alpha}} \left[\Phi^{-1} \left(\frac{\theta}{f(v)} \right) + \frac{\alpha}{\sqrt{\beta}} (z - \theta) \right] \right) \times$$

$$\times \left[\frac{1}{\phi \left(\Phi^{-1} \left(\frac{\theta}{f(v)} \right) \right) f(v)} - \frac{\alpha}{\sqrt{\beta}} \right].$$

To investigate the sign of this derivative, let's focus on

$$\frac{1}{\phi \left(\Phi^{-1} \left(\frac{\theta}{f(v)} \right) \right) f(v)} - \frac{\alpha}{\sqrt{\beta}}.$$

Since

$$\min_{\theta \in (0, f(v))} \frac{1}{\phi \left(\Phi^{-1} \left(\frac{\theta}{f(v)} \right) \right)} = \sqrt{2\pi},$$

then

$$\beta \geq \frac{\alpha^2}{2\pi} f(v)^2$$

is a sufficient condition, $\forall z$, for U to be monotonic in θ, and therefore for uniqueness of the equilibrium, given v.

Recalling that $0 \leq f(v) \leq 1 + \varepsilon$, we can obtain the following global uniqueness condition:

$$\beta \geq \frac{\alpha^2}{2\pi} (1 + \varepsilon)^2.$$

For the proof that this is the only equilibrium surviving iterated deletion of strictly dominated strategies, see Morris and Shin (2001), Morris and Shin (2003). □

3.4 Discussion on Uniqueness Condition

Let us now discuss the condition identified by *Proposition 2.* The condition, including α and β, states that public information cannot be too precise with respect to private information, in order to have uniqueness. Otherwise, public information would turn out to be too strong as a coordination device, generating multiple equilibria.

If the condition is not satisfied, then the derivative of $U(\theta)$ takes value 0 two times, as shown in the following graph.

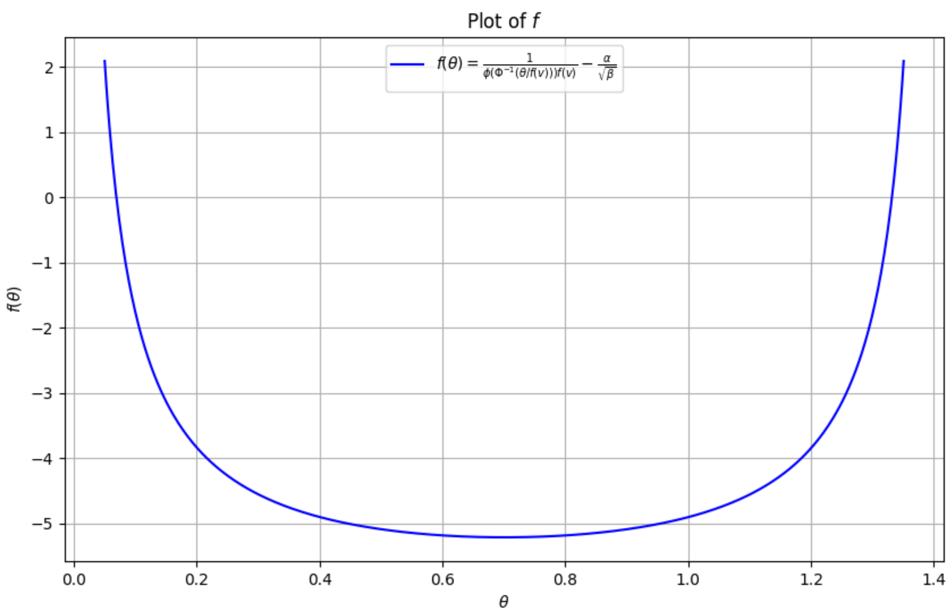

Figure 3: Relevant part of the derivative with $\alpha = 7$, $\beta = 1$, $z = 0.5$, $c = 0.4$, and $v = 1$.

This leads to a situation in which the function $U(\theta)$ shows more than one critical point. In these cases, there could be multiple equilibria, as the function $U(\theta)$ could take value 0 several times.

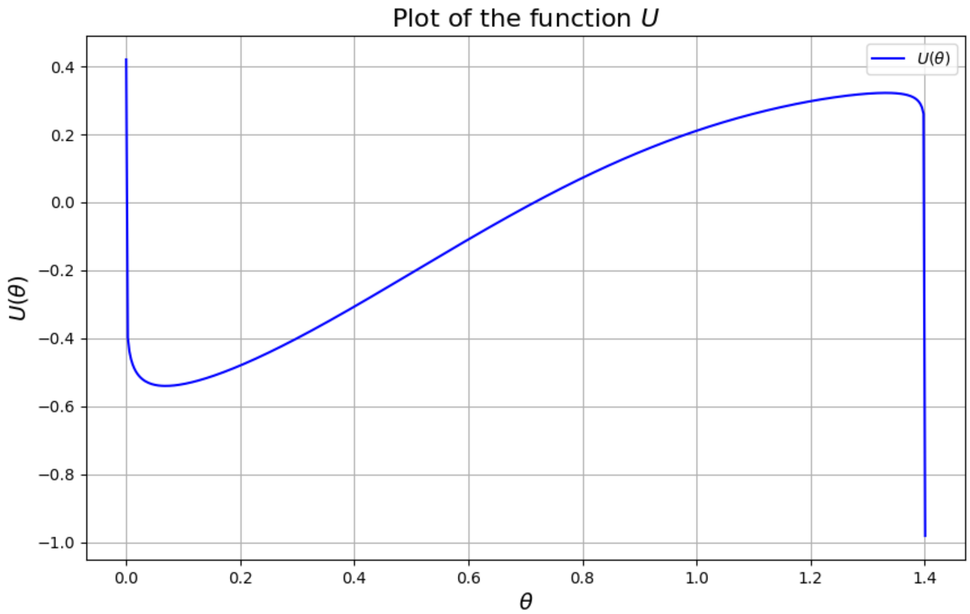

Figure 4: $U(\theta)$ with $\alpha = 7$, $\beta = 1$, $z = 0.5$, $c = 0.4$, and $v = 1$.

Note, however, that the above condition is sufficient but not necessary for uniqueness. There are cases where the first derivative of the function $U(\theta)$ takes value zero two times, where the function itself shows a maximum and a minimum, but the x-axis is only crossed once. In this scenario, there is only one equilibrium. This case is represented in the following plot.

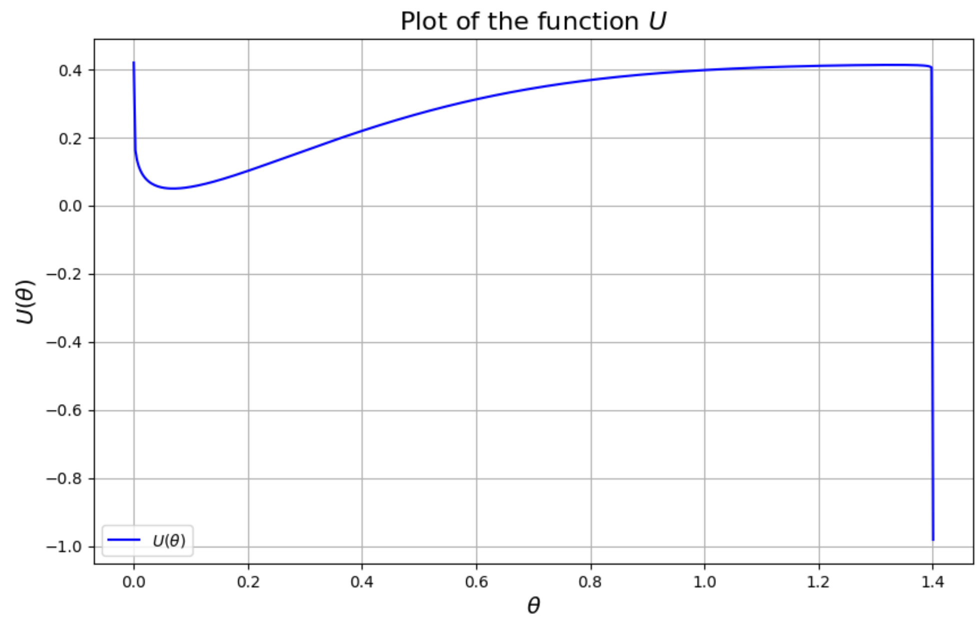

Figure 5: $U(\theta)$ with $\alpha = 7$, $\beta = 1$, $z = 0.5$, $c = 0.4$, and $v = 1$.

Let us now have a visual representation of the participation threshold as function of intensity of revolt, for a set of sensible parameters of interest. The same functional forms previously discussed and analyzed in the benchmark model with private information only is employed.

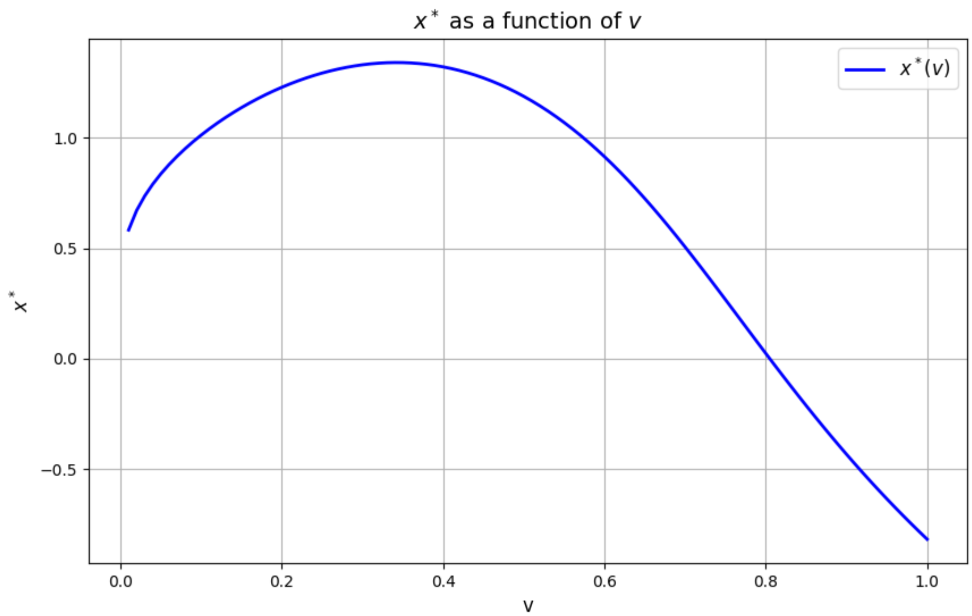

Figure 6: Participation threshold with $c = 0.4$, $z = 0.5$, $\alpha = 1$, and $\beta = 1$.

```
Maximum x* value: 1.3395
Corresponding v* value: 0.3423
```

Looking at the plot, it illustrates that in this framework the curve of $x^*(v)$, capturing aggregate participation in an attack, shows a maximum. Despite the different information structure, the behavior of $x^*(v)$ is similar to that shown in the benchmark model with private information only. This means that there exists a unique strictly positive intensity of revolt maximizing the mass of agents participating in the uprising.

4 Strategic Interaction Between Vanguard Groups

Thus far, in my analysis I have been modeling the intensity of revolt, v, as an exogenous variable of the game. It seems reasonable, however, to move a step forward and view v as the endogenous outcome of a previous part of the game.

Therefore, I now model a preceding segment of the game when more than one atomistic vanguard groups interact strategically in order to set the intensity of revolt. I proceed step by step. I begin with a benchmark model involving one single vanguard group, which serves as a reference for understanding monopoly conditions. I then investigate a Cournot-like scenario where two groups play simultaneously. For completeness, I also briefly examine the case with three simultaneous players. Finally, I explore a Stackelberg competition framework in which one vanguard group acts as a leader and the others follow sequentially. Again, I briefly investigate the three-player model, introducing an additional follower.

4.1 Intensity of Revolt Maximizing the Potential of the Attack

In previous sections, I analyzed the coordination problem of a population of agents, focusing on the participation threshold at equilibrium. When including a strategic vanguard group, however, I do not focus on the mass of protesters itself but rather on a measure of the power of the attack. I model a group aiming at maximizing the potential of the attack.

The vanguard optimizes the measure $p(v) = x^*(v) \cdot f(v)$, which captures the potential of the attack by combining the equilibrium participation threshold with the tactical multiplication effect of intensity. This formulation is particularly robust because it defines the potential of the uprising independently of the unknown fundamental θ, allowing the vanguard to make strategic decisions under incomplete information. By leveraging the direct monotonic relationship between the threshold x^* and aggregate participation, this approach maintains analytical tractability while explicitly accounting for the trade-off between increased effectiveness and the potential deterrence caused by retaliation costs.

With the usual specifications, in the simplest model with only private information the following plot is obtained:

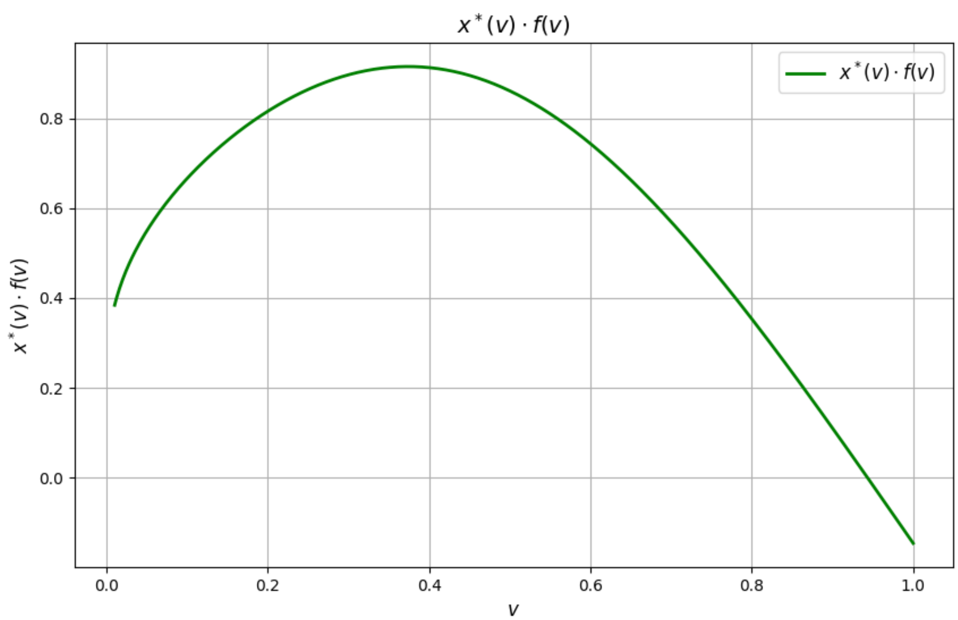

Figure 7: Potential of the attack, private information with $c = 0.4$, and $\alpha = 1$.

```
Maximum x*(v)·f(v) value: 0.9154
Corresponding v* value: 0.3739
```

Similarly, in the model with both private and public information, the following is observed:

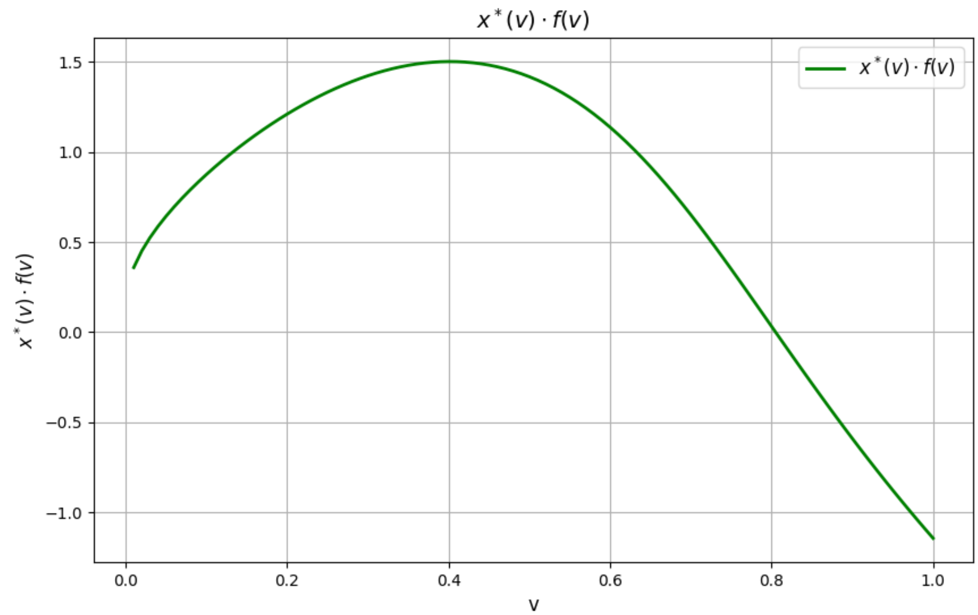

Figure 8: Potential of the attack, public and private information with $c = 0.4$, $z = 0.5$, $\beta = 1$, and $\alpha = 1$.

```
Maximum x*(v)·f(v) value: 1.5019
Corresponding v* value: 0.4017
```

Overall, as for aggregate participation, also this measure of the potential of the attack shows a maximum in both models. This means that in this case there exists a unique strictly positive intensity of revolt v that maximizes the potential of the attack.

Formally, there exists

$$v^{\text{opt}} = \arg\max_v (p(v)) = \arg\max_v \left(x^*(v) \cdot f(v)\right).$$

4.2 Strategic Interaction Between Vanguard Groups

Up to this point, I assumed an exogenously set intensity of revolt maximizing the potential of the attack. However, in fact, political violence often arises from the actions of different actors or groups, each with their own incentives and constraints.

I now proceed to model this strategic interaction. Instead of assuming that intensity of revolt is set from above, I consider how it emerges from the interplay of different vanguard groups. These groups share a common goal: they want to increase the potential of the attack. But each group must also bear the cost of its own contribution to the overall intensity of revolt.

I begin with a benchmark model involving one single atomistic vanguard group, which serves as a reference for understanding monopoly conditions. The vanguard group has utility function

$$u(v) = x^*(v) \cdot f(v) - C(v),$$

where $C(v) = v^2$ is the quadratic cost that the group pays for setting intensity of revolt. Again, I focus on $p(v) = x^*(v) \cdot f(v)$ as a measure of the potential of the attack which does not depend on the actual fundamental of the game θ, which is unknown.

The optimization of the group's utility solves

$$v^* = \arg\max_v \left[x^*(v) \cdot f(v) - C(v)\right].$$

Solving numerically (in Python with `minimize_scalar`) the vanguard's problem in a monopolistic setting yields

```
Intensity of revolt (one vanguard): 0.356
Intensity of revolt maximizing the potential of the attack: 0.4017
```

Let us now investigate the simultaneous Cournot-like interaction between two vanguard groups. The intensity of revolt will be the result of the concurring vanguard groups' choices. Each group's effort to strengthen the movement generates strategic interdependence, making the intensity of revolt an endogenous outcome of their interaction.

The total level of revolutionary activity is given by the sum of the two groups' efforts:

$$v = v_1 + v_2.$$

Each group derives utility from the expected outcome of the revolt, and faces a convex cost of exerting violence. The utility of group i is therefore defined as

$$u_i(v_i, v_{-i}) = x^*(v) \cdot f(v) - C(v_i),$$

where $v = v_i + v_{-i}$ is the total intensity of revolt and $C(v_i) = v_i^2$ represents the cost that group i incurs for its own contribution.

In the simultaneous game, each group chooses its level of violence taking the other group's action as given. The best response of group i is thus

$$v_i^* = \arg\max_{v_i} \left[x^*(v_i + v_{-i}) \cdot f(v_i + v_{-i}) - C(v_i)\right].$$

The corresponding first-order condition (FOC) for an interior optimum is

$$x^{*'}(v_i + v_{-i}) \cdot f(v_i + v_{-i}) + x^*(v_i + v_{-i}) \cdot f'(v_i + v_{-i}) - C'(v_i) = 0.$$

The Nash equilibrium of the simultaneous game is obtained by solving the system of best responses:

$$\begin{cases} v_1^* = \arg\max_{v_1} \left[x^*(v_1+v_2)\cdot f(v_1+v_2) - C(v_1)\right], \\ v_2^* = \arg\max_{v_2} \left[x^*(v_2+v_1)\cdot f(v_2+v_1) - C(v_2)\right]. \end{cases}$$

The resulting equilibrium intensities (v_1^*, v_2^*) jointly determine the total intensity of the revolt, $v^* = v_1^* + v_2^*$. Each group internalizes the cost of its own contribution but takes the other's intensity as given, leading to an overall intensity of revolt in general not optimal from the collective point of view.

Finally, individual contributions are constrained not to exceed the intensity that maximizes the overall effectiveness of the attack, v^{opt}. Excessive violence is costly and would ultimately reduce the potential of the attack, so equilibrium contributions remain below that threshold.

Now, define

$$H(v) := \frac{d}{dv}\left[x^*(v)\cdot f(v)\right] = x^{*'}(v)\cdot f(v) + x^*(v)\cdot f'(v),$$

so that the marginal benefit of an additional unit of total intensity is $H(v)$.

Let Θ denote the set of parameter values for which the potential of the attack curve $v \mapsto x^*(v)\cdot f(v)$ is single-peaked (it attains a unique interior maximum) and, moreover, $H'(v) < 0$ in a neighborhood of $v^{\max}$, where $v^{\max}$ is the unique interior maximum of $p(v)$.

Remark 1. *For the functional forms $h(v) = v^{1/3}$ and $g(v) = v^3$ adopted throughout the paper, the set Θ is non-empty whenever the uniqueness condition $\beta \geq \frac{\alpha^2}{2\pi}(1+\varepsilon)^2$ holds. To see this, note that under the uniqueness condition, $p(v) = x^*(v)\cdot f(v)$ is twice continuously differentiable by the implicit function theorem. At $v = 0^+$, the term $x^*(0)\cdot h'(0^+)$ dominates since $h'(v) = \frac{1}{3}v^{-2/3} \to +\infty$ while $g'(0) = 0$ keeps $x^{*\prime}(0^+)$ finite, so that $H(0^+) = +\infty > 0$. At $v = 1^-$, the response derivative $g'(1) = 3$ dominates $h'(1) = \frac{1}{3}$, driving $H(1^-) < 0$. By continuity of H, there exists at least one zero $v^{max} \in (0,1)$, corresponding to an interior maximum of $p(v)$. Numerical evaluation confirms that this zero is unique and that $H'(v^{max}) < 0$ across the parameter ranges of interest, as illustrated in Figures 7 and 8. Therefore the parameter configurations used throughout the paper belong to Θ, establishing $\Theta \neq \emptyset$.*

It can be shown that:

Proposition 3. *When parameters lie in Θ, the simultaneous (Cournot-like) interaction between the two vanguard groups admits a unique Nash equilibrium (v_1^*, v_2^*).*

Proof. The best response of group i solves

$$\max_{v_i} \; x^*(v_i + v_{-i}) \cdot f(v_i + v_{-i}) - C(v_i).$$

An interior optimum satisfies the first-order condition

$$H(v_i + v_{-i}) - 2v_i = 0.$$

Thus, the best-response correspondence of player i is implicitly defined by

$$G_i(v_i, v_{-i}) := H(v_i + v_{-i}) - 2v_i = 0.$$

Differentiate the implicit equation $G_i(v_i, v_{-i}) = 0$ with respect to v_{-i} to obtain the best-response slope (when the implicit function theorem applies). Denote $v = v_i + v_{-i}$. Then

$$\frac{\partial G_i}{\partial v_i} = H'(v) - 2, \qquad \frac{\partial G_i}{\partial v_{-i}} = H'(v).$$

Hence, by implicit differentiation,

$$\frac{dv_i}{dv_{-i}} = -\frac{\partial G_i / \partial v_{-i}}{\partial G_i / \partial v_i} = -\frac{H'(v)}{H'(v) - 2}.$$

Since (v_i, v_{-i}) is a Nash equilibrium with total intensity $v = v_i + v_{-i}$, and v lies in a neighborhood of $v^{\max}$, where $H'(v) < 0$ by definition of Θ, then the denominator $H'(v) - 2$ is strictly negative. Therefore, the slope $\frac{dv_i}{dv_{-i}}$ is strictly negative. That is, each player's best response is strictly decreasing in the opponent's action (the strategic substitutes property).

Consider now the composition of best response functions. Uniqueness of the fixed point (Nash equilibrium) follows if the best response map is a contraction (or, in the symmetric case, if the product of the slopes at a fixed point is strictly less than one in absolute value) (Friedman, 1977). By symmetry, the two best response slopes are equal at any symmetric profile, so it is sufficient to show

$$\left| \frac{dv_i}{dv_{-i}} \right| < 1.$$

Using the expression above and $H'(v) < 0$,

$$\left| \frac{dv_i}{dv_{-i}} \right| = \frac{-H'(v)}{2 - H'(v)}.$$

Because $-H'(v) > 0$ and $2 - H'(v) > 2$, it follows that

$$0 < \frac{-H'(v)}{2 - H'(v)} < 1.$$

Thus $|dv_i/dv_{-i}| < 1$ for all relevant v. Consequently, the best response is a contraction mapping, which implies the existence of a unique fixed point. Therefore, the simultaneous game has a unique Nash equilibrium (v_1^*, v_2^*). □

Now, it is possible to plot best response functions in order to have a visual representation of the equilibrium. I will focus on the model with both public and private information.

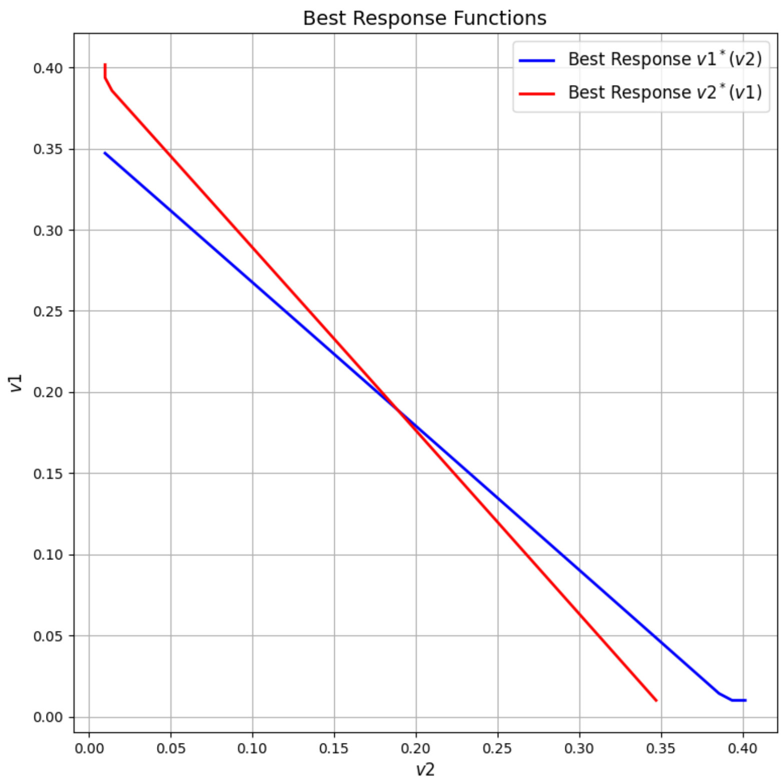

Figure 9: Cournot best responses with with $c = 0.4$, $z = 0.5$, $\beta = 1$, and $\alpha = 1$.

```
Simultaneous Cournot interaction
Vanguard 1's equilibrium intensity contribution: 0.189
Vanguard 2's equilibrium intensity contribution: 0.189
Total equilibrium intensity of revolt: 0.378
Intensity of revolt maximizing the potential of the attack: 0.4017
```

As expected, considering that vanguard groups pay a cost for the violence they express, and that they do not internalize the effect of their own contribution on the other player's payoff, the equilibrium intensity of revolt is suboptimal for maximizing the potential of the attack.

It is important to notice, however, that the equilibrium intensity of revolt with two vanguard groups contributing is higher that achieved in the one vanguard monopolistic case. Moreover, this model is helpful to make the overall intensity of revolt endogenous, and will also serve as the starting point for further analyses.

The same analysis can be extended to three vanguard groups, acting simultaneously, obtaining the following equilibrium point

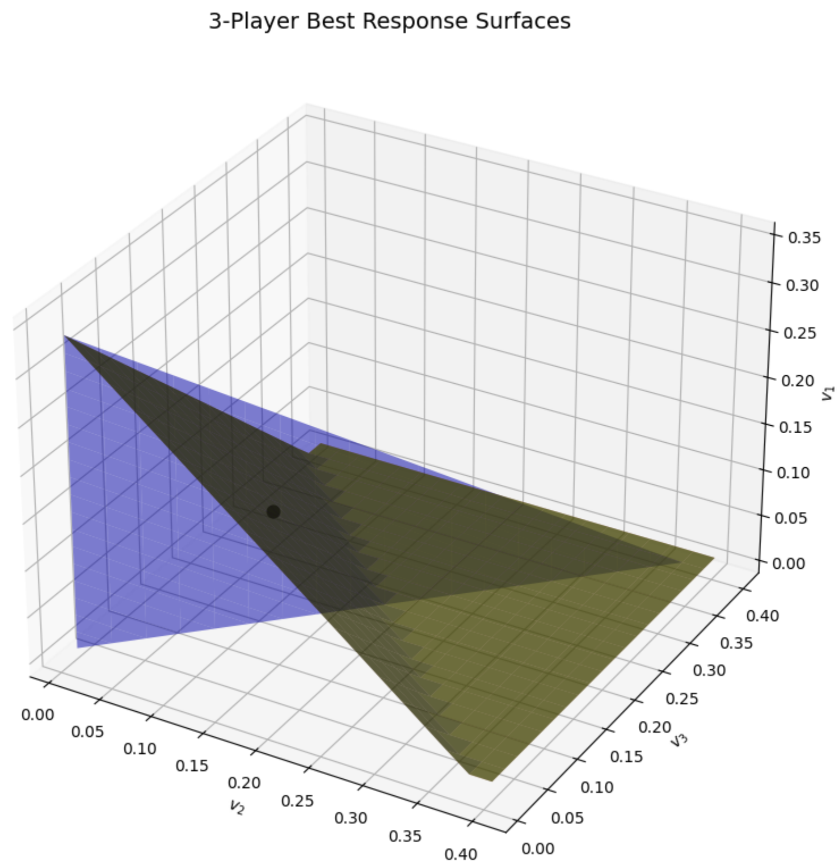

Figure 10: Cournot best responses with with $c = 0.4$, $z = 0.5$, $\beta = 1$, and $\alpha = 1$.

```
Simultaneous Cournot interaction
Vanguard 1's equilibrium intensity contribution: 0.1286
Vanguard 2's equilibrium intensity contribution: 0.1286
Vanguard 3's equilibrium intensity contribution: 0.1286
Total equilibrium intensity of revolt: 0.3857
Intensity of revolt maximizing the potential of the attack: 0.4017
```

Once again, notice that an increase in the number of vanguard groups contributing to the intensity of revolt leads to an increase in the equilibrium intensity.

Moving on, I explore a Stackelberg competition framework in which one vanguard group acts as a leader and the other follows sequentially.

Let us now consider the same setting as before, but assume that one vanguard group (group 1) acts as a leader, while the other (group 2) is a follower. The total intensity of revolt is again given by the sum of the two groups' contributions:

$$v = v_1 + v_2.$$

Each group's utility function remains

$$u_i(v_i, v_{-i}) = x^*(v) \cdot f(v) - C(v_i),$$

where $C(v_i) = v_i^2$ represents the cost paid by group i for its own contribution, and $v = v_i + v_{-i}$ is the total intensity of revolt.

Given the leader's choice v_1, the follower chooses its contribution v_2 to maximize its utility:

$$v_2^*(v_1) = \arg\max_{v_2} \big[x^*(v_1 + v_2) \cdot f(v_1 + v_2) - C(v_2)\big].$$

The follower's first-order condition (FOC) is therefore

$$x^{*'}(v_1 + v_2) \cdot f(v_1 + v_2) + x^*(v_1 + v_2) \cdot f'(v_1 + v_2) - C'(v_2) = 0.$$

This implicit equation defines the follower's best response function $v_2^*(v_1)$. Anticipating the follower's reaction, the leader chooses v_1 to maximize its own utility:

$$v_1^* = \arg\max_{v_1} \big[x^*(v_1 + v_2^*(v_1)) \cdot f(v_1 + v_2^*(v_1)) - C(v_1)\big].$$

The leader's first-order condition can be written as

$$\big[x^{*'}(v) \cdot f(v) + x^*(v) \cdot f'(v)\big] \left(1 + \frac{dv_2^*(v_1)}{dv_1}\right) - C'(v_1) = 0,$$

where $v = v_1 + v_2^*(v_1)$.

The Stackelberg equilibrium (v_1^*, v_2^*) is defined by the system

$$\begin{cases} v_2^*(v_1) = \arg\max_{v_2} \big[x^*(v_1 + v_2) \cdot f(v_1 + v_2) - C(v_2)\big], \\ v_1^* = \arg\max_{v_1} \big[x^*(v_1 + v_2^*(v_1)) \cdot f(v_1 + v_2^*(v_1)) - C(v_1)\big]. \end{cases}$$

As before, each group's individual contribution is constrained not to exceed the level of violence that maximizes the overall effectiveness of the attack, v^{opt}. Excessive violence is costly and would also reduce the potential of the attack, so equilibrium contributions remain below that threshold.

Recall

$$H(v) := \frac{d}{dv}\big[x^*(v) \cdot f(v)\big] = x^{*'}(v) \cdot f(v) + x^*(v) \cdot f'(v).$$

The same parameter set Θ as before is adopted (so that $x^*(v) \cdot f(v)$ is single-peaked and $H'(v) < 0$ on the relevant domain).

Recalling that the follower observes v_1 and chooses v_2 to solve

$$v_2(v_1) = \arg\max_{v_2} \; x^*(v_1 + v_2) \cdot f(v_1 + v_2) - C(v_2),$$

its first-order condition is

$$H(v_1 + v_2) - 2v_2 = 0.$$

Proposition 4. *Suppose parameters lie in Θ. Then the follower's best response $v_2(v_1)$ is well defined, unique and continuously differentiable for each v_1. Moreover, if the leader's objective*

$$U_1(v_1) := x^*(v_1 + v_2(v_1)) \cdot f(v_1 + v_2(v_1)) - C(v_1)$$

is strictly concave in v_1 (a sufficient condition is stated below), the Stackelberg game admits a unique subgame-perfect equilibrium (v_1^*, v_2^*).

Proof. For each fixed v_1, the follower's problem is

$$\max_{v_2} \; p(v_1 + v_2) - C(v_2),$$

recalling $p(v) = x^*(v) \cdot f(v)$. Under Θ it holds that $p''(v) = H'(v) < 0$ in a neighborhood of $v^{\max}$, ensuring local strict concavity of p for the set of relevant equilibrium values, which lie in aforementioned neighborhood. The follower's objective $p(v_1+v_2)-C(v_2)$ is therefore strictly concave in v_2 (strict concavity is preserved because $-C(v_2)$ is strictly concave), and hence admits a unique maximizer. The first-order condition

$$G(v_1, v_2) \;:=\; H(v_1 + v_2) - 2v_2 = 0$$

characterises that maximizer. The implicit function theorem applies because

$$\frac{\partial G}{\partial v_2} = H'(v_1 + v_2) - 2 < 0,$$

(the left-hand side is strictly negative since $H'(v) < 0$ and $H'(v) - 2 < 0$), so $v_2(v_1)$ is locally uniquely defined and continuously differentiable for all v_1. Differentiating the FOC gives the familiar response slope

$$\frac{dv_2}{dv_1} = -\frac{H'(v)}{H'(v) - 2},$$

with $v = v_1 + v_2$. Under Θ $|dv_2/dv_1| < 1$, so the follower responds in a well behaved way to changes in v_1.

Given the unique continuous response $v_2(v_1)$, the leader maximizes the one-dimensional problem

$$\max_{v_1} \; U_1(v_1) \;=\; \max_{v_1} \; p\big(v_1 + v_2(v_1)\big) - C(v_1).$$

A sufficient condition for uniqueness of the leader's optimiser is that U_1 be strictly concave on the feasible domain. Then the strictly concave objective admits a unique maximizer v_1^* and the corresponding $v_2^* = v_2(v_1^*)$ yields a unique Stackelberg equilibrium.

It is helpful to recall an explicit sufficient condition which one can check for given p. Differentiating once and twice (using $v = v_1 + v_2(v_1)$ and primes for derivatives of p) yields

$$U_1'(v_1) = H(v)\big(1 + v_2'\big) - 2v_1,$$

and

$$U_1''(v_1) = H'(v)\big(1 + v_2'\big)^2 + H(v)\, v_2'' - 2,$$

where, from differentiating the follower FOC twice, one obtains the closed-form expressions

$$v_2' \;=\; -\frac{H'(v)}{H'(v) - 2}, \qquad v_2'' \;=\; -\frac{4\, H''(v)}{\big(H'(v) - 2\big)^3}.$$

Thus a transparent sufficient condition for strict concavity of U_1 at the optimum (and hence uniqueness of the leader's maximizer) is the pointwise inequality

$$H'(v)\big(1 + v_2'\big)^2 + H(v)\, v_2'' - 2 < 0,$$

evaluated at $v^* = v_1^* + v_2^*(v_1^*)$. Since $H'(v^{\max}) < 0$ by definition of Θ, and the equilibrium v^* lies in a neighborhood of $v^{\max}$ where H' is continuous and strictly negative, this inequality is satisfied provided $H''(v^*)$ is not excessively large in absolute value, which can be verified directly once p is specified.

Under these hypotheses the leader's objective has a unique maximizer v_1^*. Combining this with the unique follower response $v_2(v_1^*)$ yields a unique subgame-perfect (Stackelberg) equilibrium (v_1^*, v_2^*). □

It is now worth providing a visual representation of the Stackelberg equilibrium, looking at the follower's best response and at the leader group's choice based on its anticipated payoff. I am again referring to the model with both public and private information.

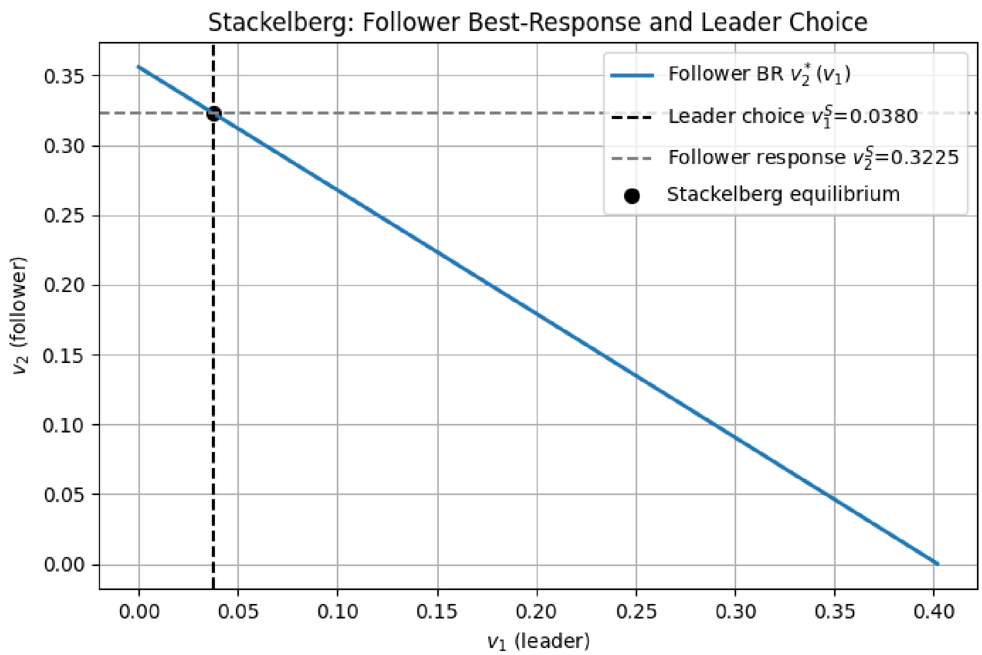

Figure 11: Stackelberg best responses with with $c = 0.4$, $z = 0.5$, $\beta = 1$, and $\alpha = 1$.

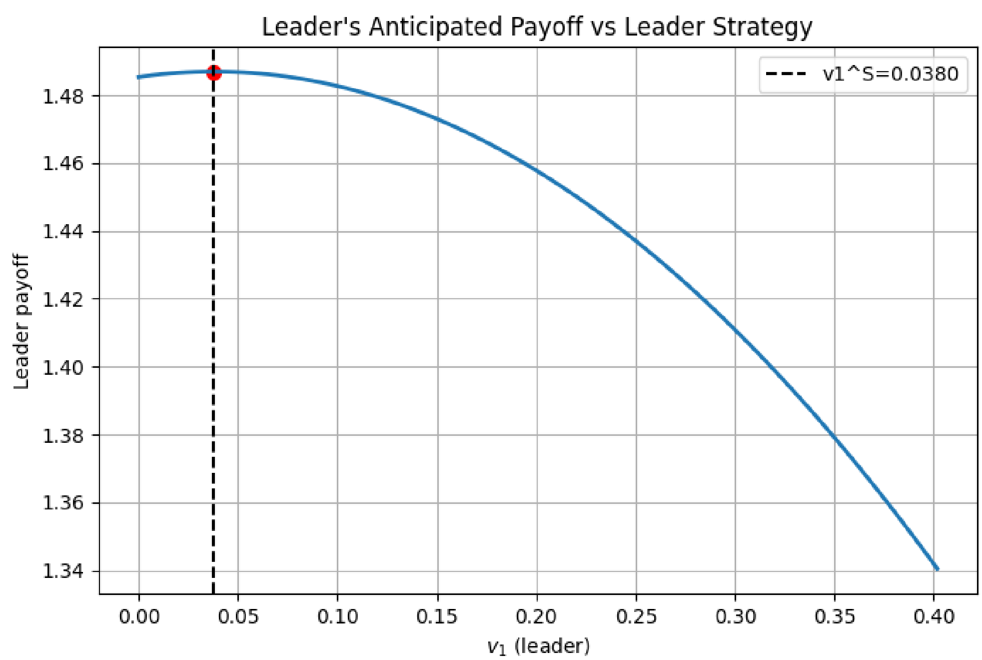

Figure 12: Stackelberg leader strategy with with $c = 0.4$, $z = 0.5$, $\beta = 1$, and $\alpha = 1$.

```
Sequential Stackelberg interaction
Leader equilibrium intensity contribution (vanguard 1): 0.0380
Follower equilibrium intensity contribution (vanguard 2): 0.3225
Total equilibrium intensity of revolt: 0.3605
Intensity of revolt maximizing the potential of the attack: 0.4017
```

The contribution costs paid by vanguard groups and the fact that they do not internalize the effect of their own contribution on the other player's payoff, yield a suboptimal intensity from the collective point of view to maximize the potential of the attack. This result is qualitatively similar to that obtained in the simultaneous move game previously investigated.

Moreover, the equilibrium intensity of revolt resulting from the sequential Stackelberg interaction is still higher than that achieved in the monopolistic benchmark model.

Let us now consider vanguard groups' payoffs

```
Payoffs at Stackelberg equilibrium
Leader payoff: 1.4869
Follower payoff: 1.3843
```

In the sequential (Stackelberg) version of the model, the entry decision of the prospective follower can be analyzed by comparing its expected payoff from entering and best-responding to the leader's strategy with its outside option. Given the leader's choice of intensity v_1, the follower optimally selects $v_2^*(v_1)$ to maximize its own payoff $u_2(v_2, v_1)$. Entry occurs only if the resulting net payoff exceeds the follower's outside option.

When considering a baseline model in which the outside option's payoff is normalized to 0, and there are no organizational costs, with this specification the follower's payoff is positive. This means that it has an incentive to enter the game.

This structure allows for the identification of a participation threshold that determines when it is rational for a secondary revolutionary group to join the game. Moreover, by comparing the follower's equilibrium payoff to the payoff it would obtain as a first mover (if it could assume the leadership role), the model can reveal whether a significant first-mover advantage exists. Hence, the framework can capture both the conditions under which subordinate revolutionary groups choose to enter and the strategic incentives that shape the internal hierarchy of revolutionary mobilization.

Formally, the follower enters the contest only if the following participation condition holds:

$$u_2\big(v_2^*(v_1), v_1\big) - C_F \geq \bar{u}_2,$$

where $\bar{u}_2$ is the follower's outside option, normalized to zero in the baseline specification, and C_F are organizational or mobilization costs. When the inequality is not satisfied, the follower optimally stays out of the game.

Furthermore, the model allows for the evaluation of a potential first-mover advantage, defined as the payoff difference between leading and following:

$$\Delta_{FM} = u_2^L - u_2^F,$$

where u_2^L represents the payoff that the same group would obtain if it acted as the leader (choosing v_2 first and anticipating the best response of the other group), and u_2^F is its equilibrium payoff as the follower. A positive Δ_{FM} indicates that anticipating the rival and committing to revolt first yields a strategic advantage, providing a formal measure of the incentive to contest leadership positions within revolutionary movements.

It is possible the extend this sequential interaction framework to three vanguard groups, with one leader and two followers, obtaining the following results.

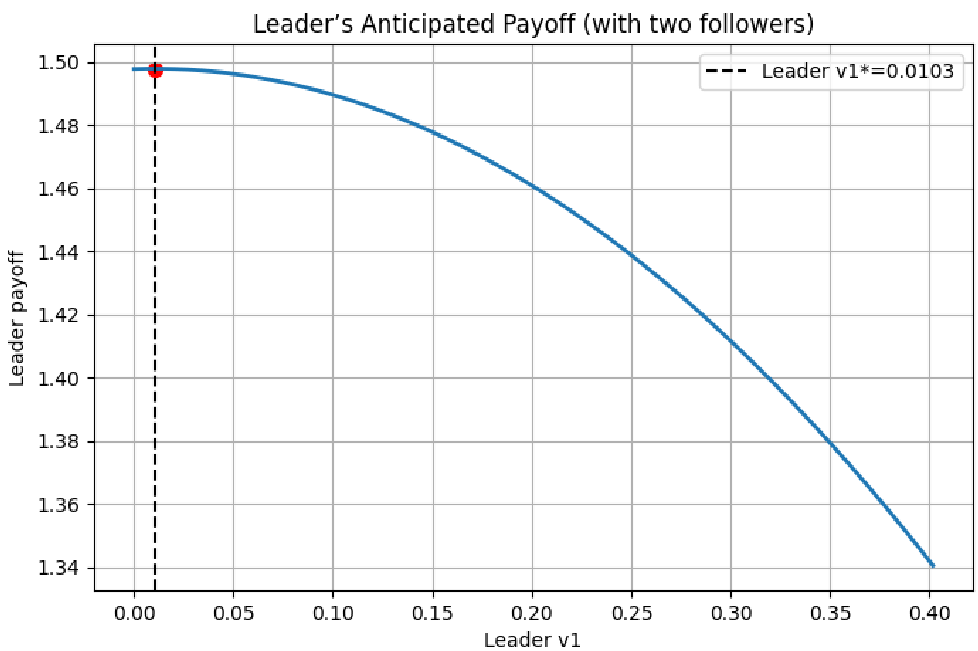

Figure 13: Best responses with with $c = 0.4$, $z = 0.5$, $\beta = 1$ and $\alpha = 1$.

```
Sequential Stackelberg interaction
Leader equilibrium intensity contribution (vanguard 1): 0.0103
Follower 1 equilibrium intensity contribution (vanguard 2): 0.1846
Follower 2 equilibrium intensity contribution (vanguard 3): 0.1846
Total equilibrium intensity of revolt: 0.3796
Intensity of revolt maximizing the potential of the attack: 0.4017
```

Notice that again an increase in the number of vanguard groups contributing to the intensity of revolt leads to an increase in the equilibrium intensity. This result is qualitatively similar in the simultaneous and in the sequential games.

The comparison between the Cournot-like and Stackelberg-like configurations highlights how the timing of strategic interaction among revolutionary groups shapes both the intensity and the effectiveness of collective action. In both cases, the presence of multiple vanguard organizations generates a higher equilibrium level of revolutionary violence than in the monopolistic benchmark, where a single actor internalizes the full cost of mobilization. However, the Cournot-like equilibrium, characterized by simultaneous decisions and strategic interdependence, leads to a higher total intensity of revolt than the sequential Stackelberg case.

Therefore, a Cournot-like interaction tends to increase the potential of the attack in contexts where, due to internalized costs and/or the relatively low number of vanguard groups, the equilibrium intensity of revolt is below the socially optimal level. In such settings, the additional intensity generated by simultaneous competition moves the system closer to the level that maximizes the potential of the attack on the regime. Conversely, in contexts where the equilibrium intensity already exceeds the optimal level, a Stackelberg-like interaction, with sequential moves and strategic moderation by the leader, produces an overall intensity that is closer to the optimum, and thus would be associated with a higher potential of the attack compared to the simultaneous-move configuration.

5 Quality of Public Information and Intensity of Revolt

At this point, I want to introduce and model the concept of quality of public information in my theoretical framework. The goal is to investigate the effects of the quality of public information on intensity of revolt, to achieve a deeper understanding of the effects of the informative environment and the possible drivers of political violence in general.

In order to do so, I intervene on the precision of the public signal. Therefore, I focus on the model with both public and private information. I model a change in the quality of public information as a different precision of the public signal. This translates into a modification of the uncertainty shared across the population, affecting the common understanding of the fundamental of the game θ.

5.1 Theoretical Formulation

I model a change in the quality of public information as a shift in the informational environment faced by individuals. Specifically, I assume that it corresponds to a shift in the precision of public signals about the fundamental state of the world θ. In Bayesian terms, this means that the component of beliefs common to all individuals becomes more or less noisy, affecting its informativeness. The result is a society in which coordination becomes more or less difficult due to a change in the precision of common knowledge, potentially amplifying uncertainty and instability.

Let us consider the implicitly defined equilibrium couple

$$\begin{cases} x^* = \dfrac{1}{\beta}\left\{\left[\theta^* - \dfrac{1}{\sqrt{\alpha+\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right)\right](\alpha+\beta) - \alpha z\right\} \\ \theta^* = f(v)\Phi\left(\dfrac{\alpha}{\sqrt{\beta}}\theta^* - \sqrt{\dfrac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right) - \dfrac{\alpha}{\sqrt{\beta}}z\right). \end{cases}$$

Formally, $v^*(\alpha)$ is defined implicitly as the solution to the optimization problem

$$v^*(\alpha) = \arg\max_v \, p(v,\alpha),$$

where the objective function is still is given by

$$p(v,\alpha) = x^*(v,\alpha) \cdot f(v),$$

a measure of the potential of the attack.

Here, $x^*(v,\alpha)$ is the equilibrium participation threshold, which depends on an implicit solution for $\theta^*(v,\alpha)$, and thus cannot be expressed in closed form. Nevertheless, under appropriate regularity conditions, the derivative $\frac{dv^*}{d\alpha}$ can be characterized using tools from implicit differentiation and the envelope theorem.

Assuming $p(v,\alpha)$ is twice continuously differentiable and that $v^*(\alpha)$ is an interior solution, the first-order condition for optimality implies

$$\frac{\partial p}{\partial v}(v^*(\alpha),\alpha) = 0.$$

Differentiating both sides of this identity with respect to α yields

$$\frac{d}{d\alpha}\left(\frac{\partial p}{\partial v}\right) = \frac{\partial^2 p}{\partial v \partial \alpha}(v^*(\alpha),\alpha) + \frac{\partial^2 p}{\partial v^2}(v^*(\alpha),\alpha) \cdot \frac{dv^*}{d\alpha} = 0,$$

which leads to the expression

$$\frac{dv^*}{d\alpha} = -\left.\frac{\frac{\partial^2 p}{\partial v \partial \alpha}}{\frac{\partial^2 p}{\partial v^2}}\right|_{v=v^*(\alpha)}.$$

To investigate the relationship between the precision of public signals α and the equilibrium intensity of revolt $v^*(\alpha)$, I implement a numerical optimization procedure. For each value of α in a specified range, I compute $v^*(\alpha)$ by maximizing the objective function $p(v,\alpha) = x^*(v,\alpha) \cdot f(v)$. Since $x^*(v,\alpha)$ depends on an implicit solution $\theta^*(v,\alpha)$, obtained via root-finding, the entire mapping must be computed numerically. The code uses a bounded scalar optimization to solve for the optimal v at each α, and then interpolates the resulting values to generate a smooth approximation of the function $v^*(\alpha)$. This approach allows me to study the comparative statics of the model even in the absence of closed-form solutions.

5.2 Strategic Effects of Public Information Precision on Intensity of Revolt

I am interested in how the intensity of revolt $v^*(\alpha)$, that is, the level that maximizes the potential of the uprising, changes with the precision of the public signal α. My analysis shows that the relationship between $v^*(\alpha)$ and α depends on the mean of the public signal about the regime's strength, denoted by z. I consider three different scenarios, low, intermediate, and high values of z, and show that they lead to different strategic incentives and patterns in $v^*(\alpha)$. When z is high (in other words, when the public signal suggests the regime is strong), $v^*(\alpha)$ is decreasing. When z is low (when the regime appears weak), $v^*(\alpha)$ is increasing. Most interestingly, when z takes intermediate values, the relationship becomes roughly U-shaped: $v^*(\alpha)$ first decreases and then increases as the precision of the public signal rises. Please note that the boundaries between these regimes are relative and depend on structural parameters, especially the cost of participation c.

The different patterns of $v^*(\alpha)$ across the three z regimes can be understood through the strategic logic of protest coordination under uncertainty, that will now be investigated.

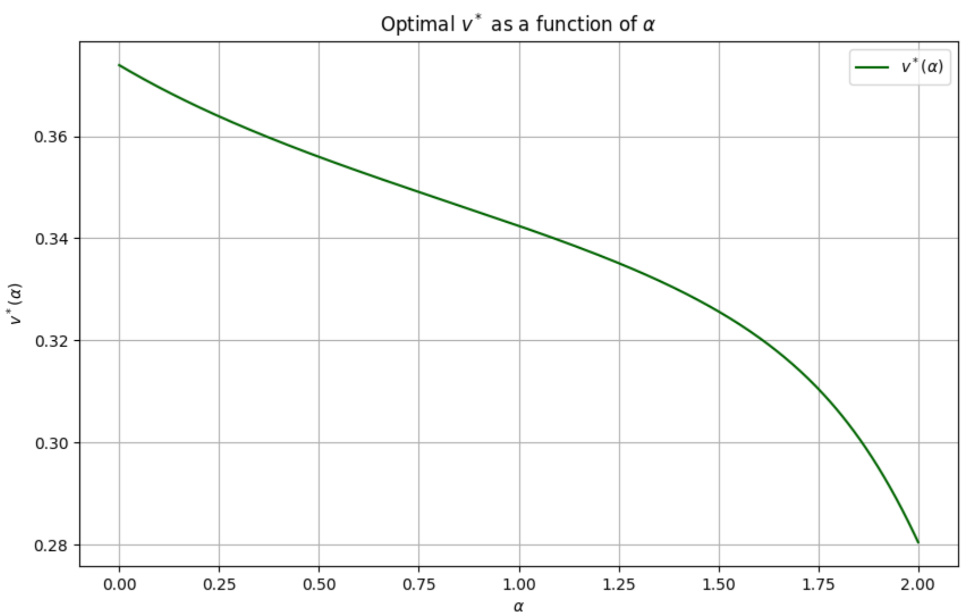

Figure 14: $v^*(\alpha)$ with $c = 0.4$, $z = 0.75$, and $\beta = 1$.

When z is high and the public signal favors the regime, increasing the precision of that signal aligns beliefs around regime strength. Citizens come to share the view that the regime is unlikely to fall, making it harder for any protest movement to be successful. In such environments, higher intensity of revolt becomes strategically less useful: it cannot overcome the common belief in regime stability, and so it is optimal to reduce its use. As a result, $v^*(\alpha)$ decreases with α.

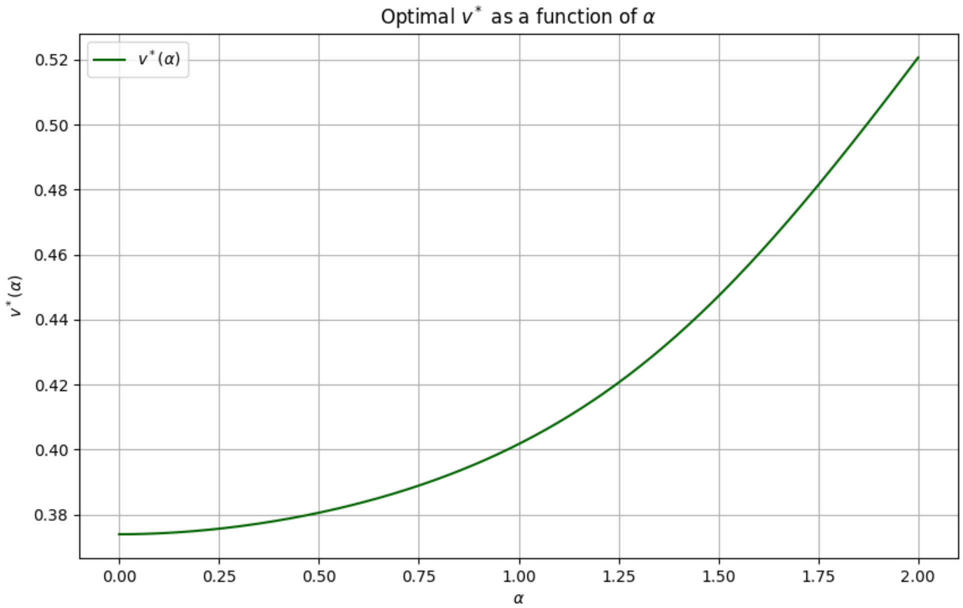

Figure 15: $v^*(\alpha)$ with $c = 0.4$, $z = 0.5$, and $\beta = 1$.

When z is low and the regime appears weak, greater public signal precision helps citizens coordinate in favor of protest. They become more confident that others also see the regime as vulnerable. In this case, the strategic benefit of an intense uprising increases with α, since it can amplify protest power in an already favorable belief environment. Here, $v^*(\alpha)$ increases as public information becomes more precise.

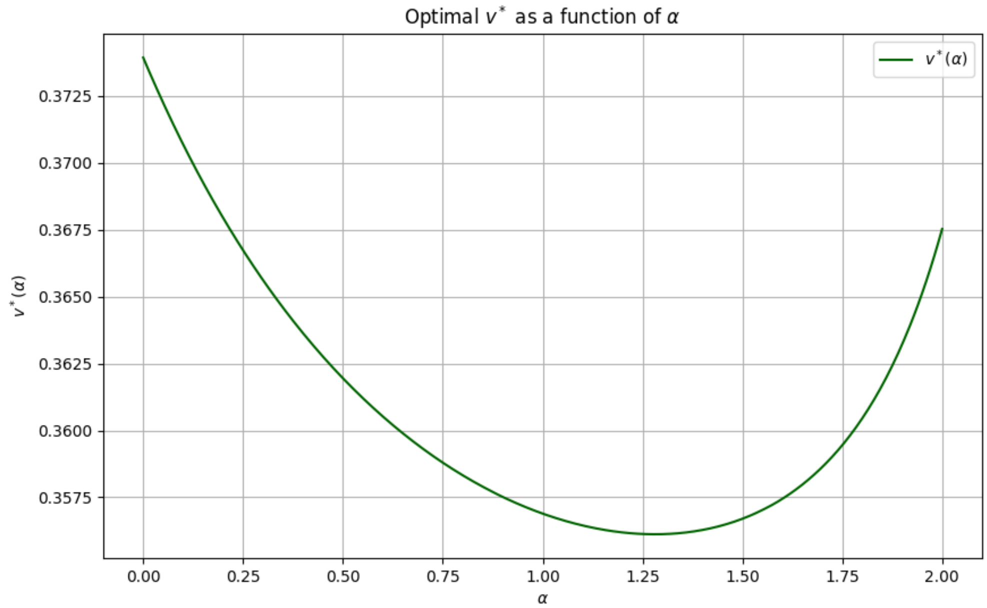

Figure 16: $v^*(\alpha)$ with $c = 0.4$, $z = 0.69$, and $\beta = 1$.

The most interesting case is when z is at an intermediate level, when the regime is perceived as neither clearly strong nor clearly weak. This is the regime in which strategic forces pull in opposing directions and where violence plays its most complex role. At low levels of α, beliefs are highly dispersed due to the dominance of noisy private signals. Citizens are unsure both about the regime's actual strength and about each other's willingness to act. In this high-uncertainty environment, higher intensity of revolt serves as a strategic coordination device. It increases the expected payoff from protesting, encouraging individuals to participate. Therefore, $v^*(\alpha)$ is initially high.

As α increases, the public signal gains weight in citizens' posterior beliefs, and their views begin to converge around the intermediate signal value. While this reduces uncertainty, it also reduces the heterogeneity of expectations that allowed some individuals to take extreme action. Now, with more moderate and aligned expectations, the willingness to protest diminishes. Therefore, an intense revolt loses some of its coordinating value, and $v^*(\alpha)$ declines.

However, as α increases further, another strategic shift takes place. With high enough precision, the public signal starts acting as a strong common knowledge device. Even if the regime appears moderately strong, citizens become more confident that others interpret the signal in the same way. Small shifts in the signal or in its interpretation can now move large fractions of the population toward action. In this new environment, the marginal value of intensity increases again. As a result, $v^*(\alpha)$

starts rising again, producing the U-shaped pattern observed.

This evolution can be understood as a transition in the strategic relationship between revolt intensity and information precision, a transition from substitute to complement. When information is scarce and private signals dominate, revolt intensity functions as a substitute for public coordination mechanisms: it conveys information about others' willingness to act and thereby facilitates collective mobilization despite dispersed beliefs. As the quality of public information improves, this substitutive role diminishes. Once the public signal attains sufficient precision to create shared expectations, intensity becomes a complement instead. Its effectiveness now derives from, and reinforces, the common informational environment. In this regime, violence amplifies rather than compensates for information, translating common knowledge into coordinated action.

In a 3-D graph the situation is illustrated.

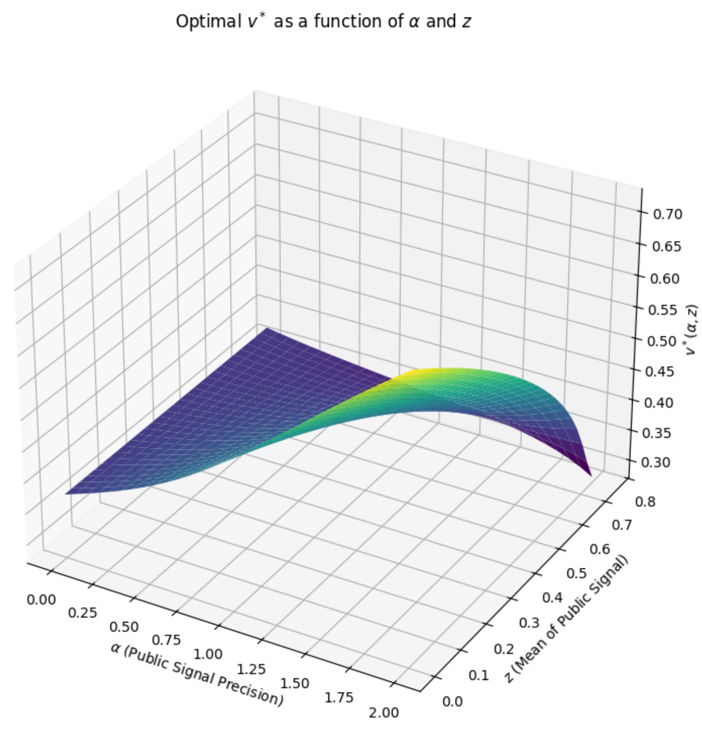

Figure 17: $v^*(\alpha, z)$ with $c = 0.4$, and $\beta = 1$.

The key takeaway from this analysis is that public information affects not just what citizens believe about the regime, but also how they coordinate with one another. In environments of very high or very low public signal means, the role of intensity is relatively straightforward: it becomes either ineffective or reinforcing, depending on the direction of beliefs. But when the signal is in the middle, the strategic value of intensity becomes nonlinear and highly sensitive to the precision of information.

This result warns against simplistic interpretations of transparency in political environments. Making information more (or less) precise does not always stabilize a regime or reduce the risk of protest. In some situations, increased precision may paradoxically restore the strategic appeal of violence and revive the potential for coordinated dissent and revolt.

5.3 Total Conflict Intensity in a Regime Change Episode

Let us now investigate the behavior of the total level of violence intensity in a revolutionary episode. This is given by the sum of vanguard-set intensity and the regime's response, $g(v)$. Despite only representing a cost in the case of a failed attack, the regime's response is always present, and therefore always contributes to the overall violence of an episode. In the following plots, we observe that the results closely follow those of $v^*(\alpha)$ alone, across all scenarios, despite differences in scale. This fact preserves our previous observations, including the ones regarding the fascinating U shape for intermediate values of the public signal.

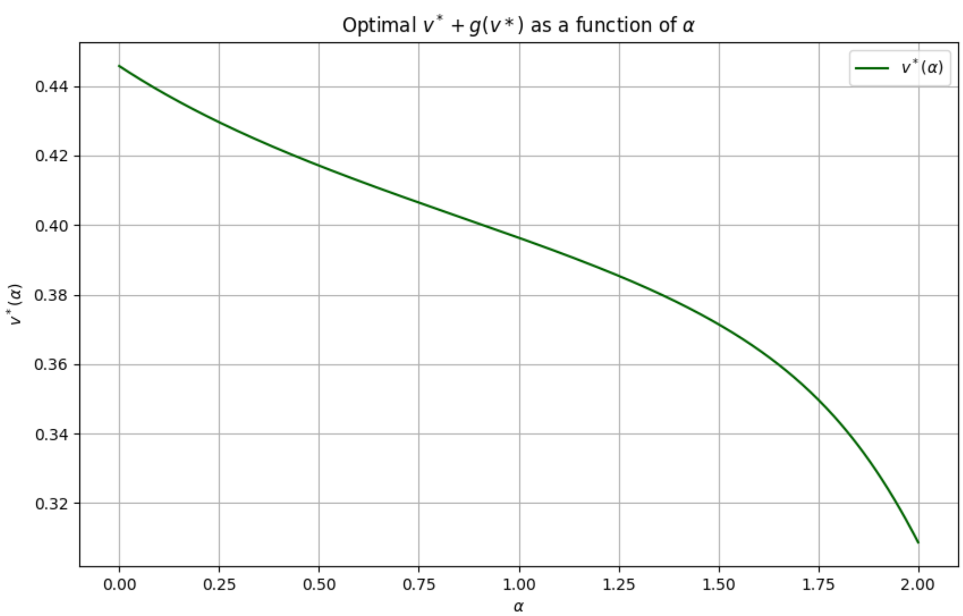

Figure 18: $v^*(\alpha) + g(v^*(\alpha))$ with $c = 0.4$, $z = 0.75$, and $\beta = 1$.

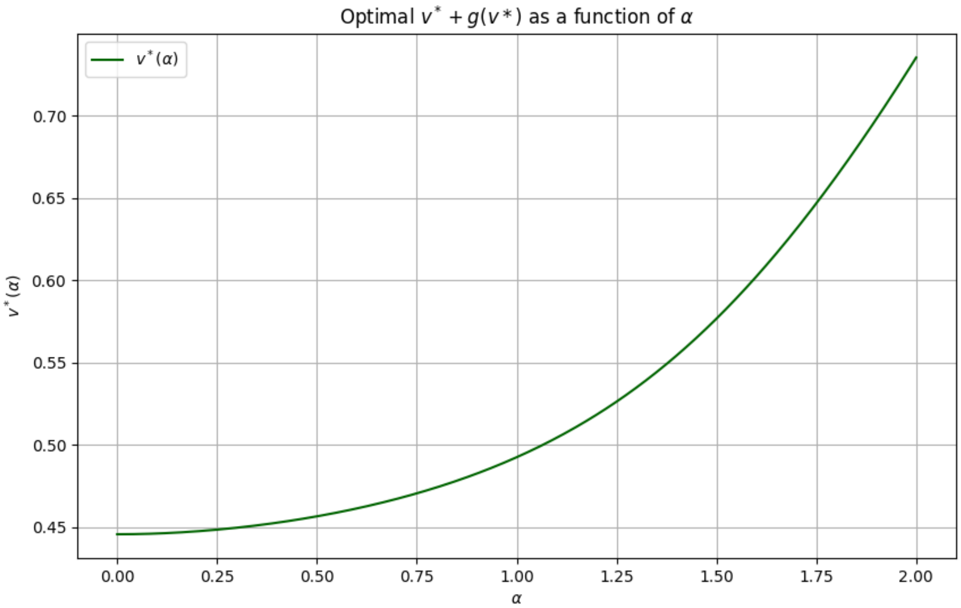

Figure 19: $v^*(\alpha) + g(v^*(\alpha))$ with $c = 0.4$, $z = 0.5$, and $\beta = 1$.

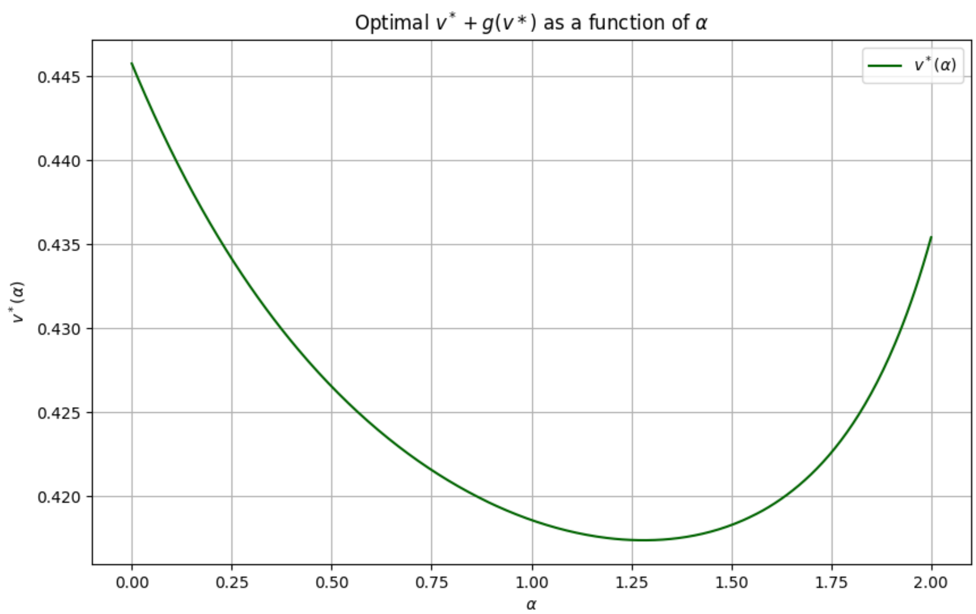

Figure 20: $v^*(\alpha) + g(v^*(\alpha))$ with $c = 0.4$, $z = 0.69$, and $\beta = 1$.

5.4 Strategic Interaction Between Vanguard Groups

In previous pages, I have studied how the quality of public information affects the intensity of revolt that maximizes the potential of the attack. In that framework, I assumed a centralized decision-maker choosing the optimal level of violence $v^*(\alpha)$ to reach that goal. However, as previously discussed and modeled, political violence often arises from the actions of different actors or groups, each with their own incentives and constraints.

One important idea I carry forward from the previous analysis is the following: if a change in the quality of private information (modeled as α) pushes the optimal intensity of revolt upward, then the strategic choices of the two groups are likely to follow that trend. In other words, when the target intensity needed for maximum potential increases, each group will be willing to contribute more, leading to a higher equilibrium level of violence.

Without repeating the technicalities that have already been stated previously, let us move on to see the equilibrium intensity and how it is affected by α, investigating the model with public and private information. I will investigate both the simultaneous and the sequential interaction configurations.

Let us start with the Cournot-like simultaneous interaction. Setting a low value of z, let us start with $\alpha = 0.3$, which is associated with a relatively low intensity of revolt that maximizes the potential of the attack. It yields

```
Simultaneous Cournot interaction
Vanguard 1's equilibrium intensity contribution: 0.1689
Vanguard 2's equilibrium intensity contribution: 0.1689
Total equilibrium intensity of revolt: 0.3378
Intensity of revolt maximizing the potential of the attack: 0.3764
```

Let us now see what happens with $\alpha = 0.5$, which is associated with a higher intensity that maximizes the potential of the attack. It yields

```
Simultaneous Cournot interaction
Vanguard 1's equilibrium intensity contribution: 0.1736
Vanguard 2's equilibrium intensity contribution: 0.1736
Total equilibrium intensity of revolt: 0.3473
intensity of revolt maximizing the potential of the attack: 0.3806
```

As anticipated, when the parameter α changes in such a way that increases the revolt intensity optimal to maximize the potential of the attack, also the equilibrium intensity resulting from the strategic interaction between two vanguard groups increases.

The same pattern can be observed when investigating a sequential Stackelberg interaction. Preserving the framework just adopted, setting $\alpha = 0.3$, which is associated with a relatively low intensity of revolt that maximizes the potential of the attack, leads to

```
Sequential Stackelberg interaction
Leader equilibrium intensity contribution (vanguard 1): 0.0167
Follower 1 equilibrium intensity contribution (vanguard 2): 0.1615
Follower 2 equilibrium intensity contribution (vanguard 3): 0.1615
Total equilibrium intensity of revolt: 0.3396
Intensity of revolt maximizing the potential of the attack: 0.3764
```

With $\alpha = 0.5$, which is again associated with a higher intensity that maximizes the potential of the attack,

```
Sequential Stackelberg interaction
Leader equilibrium intensity contribution (vanguard 1): 0.0153
Follower 1 equilibrium intensity contribution (vanguard 2): 0.1667
Follower 2 equilibrium intensity contribution (vanguard 3): 0.1667
Total equilibrium intensity of revolt: 0.3487
Intensity of revolt maximizing the potential of the attack: 0.3806
```

Again, an increase in the intensity of revolt maximizing the potential of the uprising leads to a higher endogenous equilibrium intensity.

Please note that total conflict intensity, which also accounts for the regime's response, follows the same pattern.

6 Empirical Model and Data

Drawing from the equilibrium properties derived in the theoretical model, I formulate the main predictions regarding the determinants of revolutionary violence. In particular, I consider the testable hypotheses listed below:

Hypothesis 1. *Total Revolutionary Intensity of Violence exhibits a U-shaped relationship with the Quality of Public Information. While the theoretical framework identifies this non-monotonicity under specific parameter restrictions, I argue that these conditions provide a robust approximation of real world scenarios, and I therefore focus on this specific pattern for the empirical testing.*

Hypothesis 2. *Total Revolutionary Intensity of Violence is strictly increasing in the number of Competing Vanguard Groups involved in the mobilization.*

In the following subsections, I describe the proxies for the relevant variables and the empirical strategy used to examine whether these variables have the expected effects on the intensity of the revolutionary episode.

6.1 Data

The empirical analysis draws primarily from the *Revolutionary Episodes* dataset (Version 1.0) compiled by Beissinger (2022). This dataset provides a comprehensive global catalogue of 345 mass-mobilization episodes aimed at seizing state power between 1900 and 2014. A revolutionary episode is defined as *a mass siege of an established government by its own population with the aim of displacing the incumbent regime and substantially altering the political or social order*, which aligns perfectly with my theoretical framework. I restrict the estimation sample to completed revolutionary episodes, excluding ongoing conflicts to ensure a definitive accounting of total casualties and duration. The *Revolutionary Episodes* dataset serves as the source for the dependent variable components (deaths counts and participant numbers), the proxy count of vanguard competition, and the structural controls including decades, regions of the world, and the nature of the incumbent regime (e.g., military dictatorship, monarchy, or single-party state).

To measure the information environment, I integrate the event data with the *Freedom of Expression* index from the *Varieties of Democracy* (V-Dem) project, processed by Our World in Data (V-Dem and Our World in Data, 2025). I select this source specifically for its exceptional historical depth; the V-Dem data covers the period 1789–2024, allowing us to characterize the revolutionary information environment for most episodes in the 1900–2014 Beissinger sample without excessive sample attrition. After merging the data sources and removing observations with missing or inconsistent covariates, I am left with 326 distinct episodes.

Methodologically, I address the risk of reverse causality by recording the level of freedom of expression in the year immediately preceding the start of the revolution ($t-1$). This is vital because the conflict itself often triggers a massive shock to the information environment, driving it in one of two opposing directions. On one hand, a successful movement may dismantle state censorship, leading to rapid liberalization. On the other hand, a threatened regime often responds with a repression backlash, seizing control of media and cutting off communication to survive. Because the violence itself determines whether freedom expands or contracts, I must look at the conditions before the episode began to understand what caused it.

Moreover, I restrict the sample to episodes spanning no more than three calendar years. This conservative threshold serves two key purposes. First, it ensures that the estimates capture the effects of the pre-existing information environment, limiting concerns that I am estimating the effects of how the environment itself evolves endogenously during long conflicts. Second, while excluding long-duration events, this window remains wide enough to account for episodes developing over several months, without severely compromising the sample size. Please note that a span of three years refers to calendar years; for example, an event starting in December of year $t-1$ and ending in January of $t+1$ would be recorded as 3-year episode despite lasting only 14 months. While one might argue convincingly that revolutionary events exhibit path dependence, where initial conditions influence outcomes even years later, attributing results to pre-existing conditions in episodes lasting 10 or 15 years requires very strong assumptions that I am not willing to make. This additional sample restriction leaves me with 220 revolutionary episodes drawn from the originary dataset.

Let us now explore the proxy variables that I employed in the baseline specification of my empirical investigation.

Dependent Variable (I). To test the hypotheses, it is necessary to have a measure of the total intensity of violence relative to the scale of the mobilization. According to the theoretical discussion, this measure has to capture both the contribution of the revolutionary groups and the regime's response (which are often indistinguishable in real life scenarios). I construct the dependent variable, I, as a proxy for the lethality of the revolution. Specifically, I calculate the yearly lethality ratio, defined as the number of average yearly deaths divided by the maximum number of participants, in percentage. To account for the highly skewed distribution of conflict casualties (the "fat tail" problem characteristic of violence data) and to facilitate the interpretation, I define I as the natural logarithm of this ratio:

$$I = \ln\left(\frac{\text{Average Yearly Deaths}}{\text{Participants} + 1} \cdot 100 + 1\right).$$

The inclusion of the constant (+1) serves to anchor the scale at zero and stabilize the distribution's lower bound, ensuring that episodes with marginal but positive lethality do not generate disproportionate negative values in the logarithmic transformation. I restrict my analysis to the intensive margin of violence by focusing on episodes with positive lethality ($I > 0$). This ensures that the estimates capture the dynamics of escalation within violent episodes rather than the binary strategic choice between non-violence and violence, and leaves me with 177 observations.

Independent Variables. To test Hypothesis 1, I employ a proxy for the quality and availability of public information (Q). I utilize the *Freedom of Expression* index, which captures transparency and the extent to which citizens can communicate and coordinate. It combines information on freedom of discussion, freedom of academic and cultural expression, media censorship, media self-censorship, media bias, harassment of journalists, and the existence of critical and different perspectives in print and broadcast media. I normalize this variable by dividing the raw index by its maximum observed value; thus, $Q = 0$ represents a regime with total information suppression, while $Q = 1$ represents an environment with maximal freedom of expression. Recall that I employ the index value from the year prior to the episode ($t - 1$) to avoid reverse causality, ensuring the measure reflects the pre-revolutionary environment. To test Hypothesis 2, I construct a Vanguard Competition Index (G) to capture the level of strategic rivalry among the revolution's primary power groups. I hypothesize that violence increases when the revolutionary field is crowded by multiple "strong" organizations competing, and decreases when these rivals are bound by institutionalized cooperation. The index is calculated as:

$$\text{Index }(G) = (\text{Vanguard} + \text{LibMvmt} + \text{Paramil} + \text{Underground}) - \text{Coalition}.$$

The four positive components, Vanguard parties, Liberation Movements, Paramilitaries, and Underground cells, represent the "vertical" dimension of the revolution: they are distinct, organized hierarchies capable of autonomous strategic action. A higher score indicates a fragmented competitive landscape where multiple such groups act strategically, creating incentives for escalation. I subtract Coalition (capturing whether revolutionary contention was coordinated by a coalitional leadership) because it serves as the institutional mechanism that resolves this competition, transforming rival hierarchies into partners and reducing the strategic drive for violence. I exclude leadership categories such as Youth and Unions because, in Beissinger (2022)'s framework, they represent generic, horizontal, and structurally weak leadership forms. Unlike the vertical hierarchies of vanguard or paramilitary groups, these categories lack the strict chain of command and organizational coherence necessary to function as independent strategic competitors in the struggle for regime change. Thus, the index isolates the specific competition between organized, hierarchical groups.

Control Variables. To isolate the effects of information and group competition, I include a robust set of control variables across all specifications. I employ decade fixed effects to control for global trends in technology and warfare (e.g., the Cold War era). Given the scarcity of consistent historical GDP data for non-Western states prior to 1950, I employ region fixed effects as a comprehensive control for structural heterogeneity. These fixed effects absorb a wide range of time-invariant unobserved factors specific to different parts of the world. Crucially, this approach captures not only broad cross-sectional differences in economic development (such as the gap between the Global North and South) but also underlying cultural, historical, and institutional disparities that are likely correlated with both the information environment and revolutionary dynamics. I also include dummy variables for incumbent regime types (military dictatorships, monarchies, single-party states, and competitive authoritarian regimes) to account for the repressive capacity of the state, and controls for the specific ruling situation of a regime (number of years incumbent regime rule endured prior to onset of the episode, number of years that the incumbent leader was in power at the onset of the episode, and age of incumbent leader at the onset of the episode). Finally, I control for the context of the revolutionary episode, with a dummy indicating whether the event happened in a colony, capturing possible imperial-specific or decolonization dynamics, and a second one capturing whether it was a primary urban revolution, a key feature of revolutionary episodes according to Beissinger (2022). I deliberately decide to not include country fixed effects due to the limited number of observations per country; since many nations in the sample experienced only a single revolutionary episode, introducing country-specific fixed effects would severely reduce the variation available for estimation.

In all regression specifications, Europe serves as the excluded reference category for the regional fixed effects. I selected Europe as the baseline because, descriptively, it exhibits the lowest overall (in the whole dataset) average violence intensity among all regions in the sample. This choice facilitates interpretation, as the coefficients for all other regions can be read directly as the relative increase in violence intensity compared to the most peaceful regional benchmark.

6.2 Econometric Specification

To empirically test the theoretical predictions derived in the previous sections, I formulate two distinct regression models. These specifications are designed to isolate the intensive margin of revolutionary violence.

To test Hypothesis 1, which predicts a non-monotonic U-shaped relationship between Quality of Public Information and Intensity, I specify the following quadratic equation:

$$I_i = \alpha + \beta_1 Q_i + \beta_2 Q_i^2 + \mathbf{Z}_i' \lambda + \varepsilon_i$$

where i denotes the individual revolutionary episode and I_i represents the Total Intensity (yearly log lethality). The variable Q_i denotes the normalized Information Quality index. To validate the U-shaped hypothesis, I expect the coefficients to exhibit the following sign pattern: $\beta_1 < 0$ and $\beta_2 > 0$. A negative linear coefficient indicates that violence initially decreases as information improves from total suppression, while a positive quadratic coefficient captures the convexity of the curve. Furthermore, to confirm that the relationship is truly non-monotonic within the relevant range, I verify that the estimated turning point ($-\beta_1/2\beta_2$) lies strictly within the domain of my data ($Q \in [0, 1]$).

To test Hypothesis 2, regarding the effect of competing groups, I specify the following linear equation:

$$I_i = \alpha + \gamma G_i + \mathbf{Z}_i' \lambda + \varepsilon_i$$

where G_i denotes the proxy count of competing vanguard groups involved in the mobilization (Vanguard Competition Index). I expect the coefficient γ to be positive ($\gamma > 0$), implying that greater internal competition among revolutionary factions is associated with higher intensity.

In both specifications, $\mathbf{Z}_i$ represents the vector of control variables, including incumbent regime characteristics, temporal periods, regional indicators, and context. α is the intercept, and ε_i captures the idiosyncratic error.

6.3 Estimation Strategy

In my baseline estimation of the specifications I employ Ordinary Least Squares (OLS). My estimation strategy relies on a robust fixed-effects framework to identify the coefficients of interest while mitigating omitted variable bias. Moreover, to account for potential heteroskedasticity in the error term (ε_i), a common feature in conflict data where the variance of intensity may differ across regions or regime types, I report heteroskedasticity-robust standard errors (Huber-White) in all specifications.

7 Main Results

This section presents the main empirical findings regarding the determinants of revolutionary violence intensity. I proceed by formally testing my two central hypotheses using the fixed-effects framework outlined previously. First, I examine the non-monotonic relationship between information quality and violence (Hypothesis 1), assessing the presence of the predicted U-shaped curve. Second, I analyze the impact of opposition competition on conflict intensity (Hypothesis 2). For each hypothesis, I adopt a stepwise estimation strategy, beginning with baseline bivariate specifications and progressively introducing temporal, regional, institutional, and contextual controls to verify the robustness of the estimates.

Table 2: The Non-Monotonic Effect of Information on Total Intensity

Dep var: *Yearly Deaths Index (I)*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	-4.50**	-4.71**	-6.47**	-5.21***
	(2.17)	(2.09)	(2.51)	(1.76)
Freedom of Expression Sq. (Q^2)	3.88*	4.69**	7.41***	5.35***
	(2.21)	(2.09)	(2.65)	(1.91)
Region Fixed Effects				
Asia		0.46	0.49	0.20
		(0.38)	(0.41)	(0.32)
Latin America & Carib.		0.33	0.19	-0.50
		(0.39)	(0.45)	(0.36)
Middle East & N. Africa		0.87*	1.09**	0.99**
		(0.46)	(0.50)	(0.42)
Pacific & Oceania		3.58***	2.96***	0.67
		(0.77)	(0.87)	(0.87)
Sub-Saharan Africa		1.51***	1.57***	0.20
		(0.52)	(0.51)	(0.42)
Regime Type Controls				
Democracy			-1.11*	-0.69
			(0.63)	(0.54)
Military			0.20	0.11
			(0.70)	(0.53)
Monarchy			-0.46	-0.56
			(0.65)	(0.58)
Communist			0.45	-0.05
			(0.76)	(0.55)
One-Party			-0.17	-0.10
			(0.72)	(0.57)
Comp. Authoritarian			0.29	-0.13
			(0.51)	(0.44)
Contextual Controls				
Colony				-1.33**
				(0.62)
Urban				-2.91***
				(0.28)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	173	173	173	173
R^2	0.04	0.23	0.30	0.60
Turning Point (Q)	0.58	0.50	0.44	0.49

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category.

Table 2 reports the baseline estimates for the relationship between the Quality of Public Information and Total Revolutionary Intensity. The results strongly support Hypothesis 1, revealing a robust U-shaped pattern across all specifications. In the bivariate specification (Column 1), the predicted signs are observed: a negative linear coefficient and a positive quadratic term, both significant. The explanatory power of information alone is modest, as is expected given the complexity of revolutionary dynamics, but the picture becomes clearer as I introduce controls. Columns (2) and (3) add regional and regime fixed effects, and the most significant shift occurs in Column (4) with the inclusion of contextual variables (Colony and Urban status).

The stability of these estimates is particularly informative given the model's behavior regarding fit. While the inclusion of contextual controls in Column (4) drives a substantial increase in R^2 (rising to 0.60), the coefficients for Freedom of Expression (Q) remain remarkably stable. Moreover, estimates are significant across all specification, reaching a 1% confidence level for both the linear and quadratic terms in the fully specified model. This pattern, where the explanatory power of the model increases dramatically while the coefficient of interest remains stable and highly significant, is a strong indicator of robustness. It suggests that the observed non-monotonic relationship is not driven by omitted variables.

The turning point analysis further validates the hypothesis. Across all columns, the inflection point consistently falls near the center of the unit interval. In the full specification (Column 4), the turning point is 0.49. This further confirms that the U-shape is present. The estimates imply that starting from an environment of low information quality, improvements in transparency reduce lethality until the environment reaches intermediate levels. Beyond this threshold, however, the relationship inverts, and higher transparency is associated with an increase in violence intensity.

Finally, the control variables in the full model offer important insights. The large, negative coefficient on the Urban dummy (-2.91, $p < 0.01$) dominates the specification, suggesting that urban revolutions are significantly less lethal than rural episodes. Colony is negative and significant as well, despite a lower magnitude and confidence level. It is interesting to follow the evolution of the regional controls: while the Pacific and Sub-Saharan Africa regions appear significant in Columns (2) and (3), these effects vanish in the full model, suggesting that the apparent regional differences were actually driven by underlying structural factors. Only Middle East & North Africa shows a significantly higher intensity with respect to Europe in the full model. Similarly, the coefficients for specific regime types are statistically indistinguishable from zero in the full model, suggesting that the intensity of violence is driven more by the environment of the uprising than by the formal institutional label of the incumbent.

Table 3: The Linear Effect of Vanguard Competition on Total Intensity

Dep var: *Yearly Deaths Index (I)*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	1.12***	0.89***	0.86***	0.43***
	(0.15)	(0.17)	(0.18)	(0.15)
Region Fixed Effects				
Asia		0.40	0.39	0.13
		(0.35)	(0.36)	(0.30)
Latin America & Carib.		0.36	0.17	-0.48
		(0.38)	(0.43)	(0.35)
Middle East & N. Africa		0.68	0.86*	0.91**
		(0.45)	(0.48)	(0.39)
Pacific & Oceania		2.51***	2.75***	0.59
		(0.73)	(0.80)	(0.75)
Sub-Saharan Africa		1.50***	1.48***	0.19
		(0.44)	(0.46)	(0.40)
Regime Type Controls				
Democracy			-0.38	-0.29
			(0.51)	(0.43)
Military			0.53	0.35
			(0.62)	(0.52)
Monarchy			-0.54	-0.68
			(0.63)	(0.60)
Communist			0.49	0.16
			(0.76)	(0.60)
One-Party			0.03	0.09
			(0.66)	(0.58)
Contextual Controls				
Colony				-0.95
				(0.59)
Urban				-2.78***
				(0.29)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	177	177	177	177
R^2	0.19	0.32	0.35	0.60

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category.

Table 3 presents the results regarding the impact of opposition fragmentation on Total Revolutionary Intensity (Hypothesis 2). I estimate the linear specification described above, where the variable of interest is the Vanguard Competition Index (G). The results provide strong empirical support for the hypothesis that violence is strictly increasing in the number of competing vanguard groups.

Across all four specifications, the coefficient on the Vanguard Competition Index is positive and statistically significant at the 1% level. In the baseline bivariate model (Column 1), a one-unit increase in the index is associated with a 1.12 increase in the yearly log lethality ratio. As I introduce controls for region and regime type in Columns (2) and (3), the coefficient remains relatively high (0.89 and 0.86, respectively). In the fully specified model (Column 4), the inclusion of contextual controls leads to an attenuation of the magnitude to 0.43, yet the estimate remains positive and statistically highly significant ($p < 0.01$). This attenuation suggests that while some of the initial correlation is driven by the structural environment, a significant portion of the violence is directly explained by the internal dynamics of competition.

The behavior of the model fit follows my findings for Hypothesis 1 and speaks to the robustness of the estimates. The R^2 increases substantially from 0.19 in the baseline to 0.60 in the full model, driven largely by the explanatory power of the contextual variables. The fact that the coefficient of interest survives (without losing significance) the inclusion of these powerful controls, which absorb nearly 60% of the variation in the dependent variable, provides reassurance regarding the identification strategy. It implies that the competitive incentives for violence described in the theoretical framework operate independently of the broader structural context of the revolution.

In terms of economic magnitude, the effect is substantial. The estimate from Column (4) implies that, holding the information environment and regime type constant, the entry of an additional competing vanguard group is associated with an approximate 0.43 log point increase in the lethality ratio. This confirms the mechanism that distinct, hierarchical power centers create structural incentives for escalation that are absent in coalitional or horizontal leadership structures.

Finally, the control variables behave consistently with the patterns observed in the previous analysis. The Urban dummy remains the strongest predictor of reduced lethality (-2.78, $p < 0.01$), indicating that the negative correlation between urbanization and violence is robust. Similarly, the Middle East & North Africa region again exhibits a positive and significant residual effect (0.91), while other regional and regime controls lose significance in the full model.

8 Robustness Checks

In this section, I conduct a series of tests to verify the stability and validity of the main findings. I proceed in four steps. First, I check the marginal effect and formally test the structural validity of the non-monotonic relationship using the Lind and Mehlum (2010) test to confirm the presence of a U-shaped curve. Second, I assess measurement validity by employing alternative proxies for violence intensity that account for the scale and duration of conflict. Third, I test for sample sensitivity by excluding episodes taking place in colonies, to ensure results are not driven by the unique dynamics of decolonization, and events taking place in democracies, to focus on the autocratic environment. Finally, I employ robust regression techniques to mitigate the influence of potential outliers.

8.1 Structural Validity

I begin by formally testing the validity of the non-monotonic relationship between information quality and intensity. A common critique of quadratic specifications is that a significant squared term may merely capture a monotonic relationship with diminishing returns, rather than a genuine turning point. To address this, I employ the test proposed by Lind and Mehlum (2010), which verifies whether the slope of the curve effectively changes sign within the observed data range.

The results, presented in Table 4, strongly support the presence of a U-shaped relationship. As already seen, the estimated turning point is located at $Q = 0.49$, strictly within the unit interval of my data. Crucially, the test rejects the null hypothesis of monotonicity ($p = 0.009$). It shows that the slope at the lower bound of the data interval ($Q \approx 0.02$) is negative and statistically significant ($\beta_{lower} = -4.96$, $p < 0.01$), while the slope at the upper bound ($Q \approx 1.00$) is positive and significant ($\beta_{upper} = 5.49$, $p < 0.01$). This confirms that the relationship is not merely convex but strictly non-monotonic.

Table 4: Test for U-Shaped Relationship (Lind & Mehlum, 2010)

Test Parameter	Estimate	t-value	$P > \|t\|$
Slope at Lower Bound ($Q \approx 0.02$)	-4.96	-2.95	0.002
Slope at Upper Bound ($Q \approx 1.00$)	5.49	2.38	0.009
Overall Test of U-Shape		2.38	0.009
Estimated Turning Point	0.49		

Notes: The null hypothesis is that the relationship is monotone or inverse U-shaped. Rejection of the null ($p < 0.01$) confirms the presence of a U-shaped relationship. The test is performed on the fully specified model.

This dynamic is visualized in Figure 21, which plots the marginal effect of information quality on violence intensity. The solid line represents the instantaneous slope of the curve. Consistent with the theoretical expectations, the marginal effect is negative and significant at low levels of information (where the confidence interval is strictly below zero), crosses the horizontal axis at the turning point ($Q = 0.49$), and becomes positive and significant at high levels of information. This visual evidence reinforces that intensity is minimized in semi-transparent environments, while both total suppression and total transparency are associated with significantly higher conflict intensity.

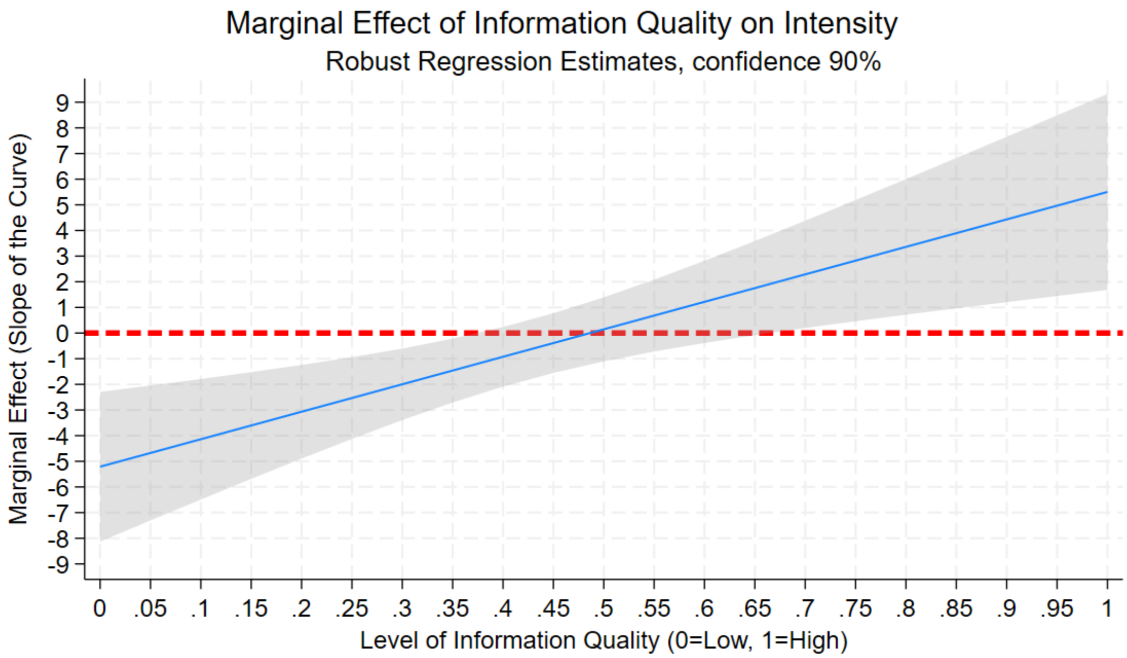

Figure 21: Marginal Effect of Information Quality on Total Violence Intensity

Notes: The figure displays the marginal effect derived from the baseline OLS model with robust standard errors. The gray area indicates the 90% confidence interval. The effect is significant where the confidence interval does not overlap with the zero line.

8.2 Alternative Measures of Total Intensity

Second, I verify that my results are not driven by the specific construction of the primary dependent variable (the yearly lethality ratio). I replicate the analysis using two alternative proxies for total violence intensity. The first is a Total Deaths Index, defined as

$$I = \ln\left(\frac{\text{Total Deaths}}{\text{Participants} + 1} \cdot 100 + 1\right).$$

which, relying on total deaths and not on a yearly average, is taking into account (not discounting it with yearly averages) the duration of the conflict in the intensity measure. The second is a Categorical Scale of Death Magnitude (*Deathscat*), an ordinal variable ranking the event's violence already built in the Beissinger (2022) dataset. This measure captures the gross magnitude of violence without relying on participant data, and the categories are defined as follows: (1) $<= 10$; (2) > 10 and $<= 100$; (3) > 100 and $<= 1000$; (4) > 1000 and $<= 10000$; (5) > 10000 and $<= 50000$; (6) > 50000. Results are robust to these alternative intensity specifications.

Robustness of Hypothesis 1

I first test the robustness of the U-shaped relationship between information quality and intensity. Table 5 presents the estimates using the Total Deaths Index. The results confirm a highly significant non-monotonic relationship. In the fully specified model (Column 4), the linear coefficient is negative ($\beta_1 = -5.73$, $p < 0.01$) and the quadratic term is positive ($\beta_2 = 5.86$, $p < 0.01$). The estimated turning point is $Q = 0.49$. This suggests that the non-monotonic effect is robust to accounting for conflict duration.

Table 5: Robustness H1: Total Deaths Index

Dep var: *Total Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	-4.42*	-4.83**	-7.13***	-5.73***
	(2.30)	(2.27)	(2.70)	(1.78)
Freedom of Expression Sq. (Q^2)	3.82	4.92**	8.13***	5.86***
	(2.36)	(2.28)	(2.83)	(1.93)
Region Fixed Effects				
Asia		0.50	0.51	0.16
		(0.42)	(0.44)	(0.34)
Latin America & Carib.		0.42	0.25	-0.51
		(0.44)	(0.51)	(0.40)
Middle East & N. Africa		0.97**	1.15**	1.02**
		(0.49)	(0.53)	(0.44)
Pacific & Oceania		3.45***	2.69***	0.11
		(0.83)	(0.93)	(0.89)
Sub-Saharan Africa		1.69***	1.77***	0.21
		(0.56)	(0.55)	(0.45)
Regime Type Controls				
Democracy			-1.30*	-0.78
			(0.68)	(0.54)
Military			0.07	0.03
			(0.77)	(0.56)
Monarchy			-0.52	-0.55
			(0.69)	(0.59)
Communist			0.32	-0.25
			(0.80)	(0.57)
One-Party			-0.31	-0.15
			(0.77)	(0.58)
Contextual Controls				
Colony				-1.32**
				(0.65)
Urban				-3.26***
				(0.28)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	173	173	173	173
R^2	0.03	0.22	0.30	0.62
Turning Point (Q)	0.58	0.49	0.44	0.49

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category.

Table 6 repeats the analysis with Categorical Scale of Death Magnitude. The findings are also consistent with the main results. The turning point in the full model is 0.62, and both coefficients are statistically significant, despite a lower confidence level.

Table 6: Robustness H1: Categorical Scale of Death Magnitude

Dep var: *Category*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	-1.41	-2.51*	-3.96**	-3.43**
	(1.46)	(1.47)	(1.69)	(1.35)
Freedom of Expression Sq. (Q^2)	0.44	1.93	3.43*	2.77*
	(1.52)	(1.53)	(1.78)	(1.42)
Region Fixed Effects				
Asia		0.47	0.31	0.31
		(0.30)	(0.28)	(0.28)
Latin America & Carib.		-0.26	-0.48	-0.48
		(0.36)	(0.31)	(0.31)
Middle East & N. Africa		0.64*	0.60*	0.60*
		(0.36)	(0.34)	(0.32)
Pacific & Oceania		1.03*	-0.52	-0.52
		(0.61)	(0.60)	(0.57)
Sub-Saharan Africa		0.96***	0.21	0.21
		(0.35)	(0.31)	(0.31)
Regime Type Controls				
Democracy			-0.14	-0.33
			(0.44)	(0.49)
Military			-0.28	-0.31
			(0.38)	(0.43)
Monarchy			-0.57	-0.81*
			(0.42)	(0.45)
Communist			0.11	0.43
			(0.50)	(0.58)
One-Party			-0.49	-0.65
			(0.44)	(0.49)
Contextual Controls				
Colony				-0.71
				(0.43)
Urban				-1.77***
				(0.21)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	206	206	206	206
R^2	0.04	0.25	0.29	0.48
Turning Point (Q)	1.60	0.65	0.58	0.62

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category.

Robustness of Hypothesis 2

I next examine the sensitivity of Hypothesis 2 using the same alternative proxies. Table 7 reports the results for the Total Deaths Index. The coefficient for the Vanguard Competition Index (G) is positive and highly significant across all specifications ($\gamma = 0.44$, $p < 0.05$ in the full model), providing strong support for the hypothesis. This reinforces the main findings, suggesting that the impact of fragmentation on intensity is positive also when accounting for duration of the episode.

Table 7: Robustness H2: Total Deaths Index

Dep var: *Total Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	1.20***	0.97***	0.91***	0.44**
	(0.16)	(0.19)	(0.20)	(0.17)
Region Fixed Effects				
Asia		0.44	0.39	0.08
		(0.38)	(0.39)	(0.33)
Latin America & Carib.		0.45	0.21	-0.50
		(0.44)	(0.49)	(0.39)
Middle East & N. Africa		0.73	0.91*	0.94**
		(0.48)	(0.51)	(0.41)
Pacific & Oceania		2.34***	2.46***	0.01
		(0.78)	(0.86)	(0.77)
Sub-Saharan Africa		1.69***	1.67***	0.19
		(0.48)	(0.50)	(0.43)
Regime Type Controls				
Democracy			-0.51	-0.34
			(0.57)	(0.47)
Military			0.42	0.28
			(0.69)	(0.56)
Monarchy			-0.66	-0.74
			(0.69)	(0.64)
Communist			0.39	0.01
			(0.81)	(0.62)
One-Party			-0.11	0.05
			(0.71)	(0.60)
Contextual Controls				
Colony				-0.92
				(0.62)
Urban				-3.14***
				(0.31)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	177	177	177	177
R^2	0.19	0.31	0.35	0.61

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category.

Finally, Table 8 presents the results for the Categorical Scale of Death. The coefficient remains consistently positive and statistically highly significant across all specifications, including the fully specified model ($\gamma = 0.39$, $p < 0.01$).

Table 8: Robustness H2: Categorical Scale of Death

Dep var: *Category*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	0.85***	0.65***	0.62***	0.39***
	(0.11)	(0.13)	(0.13)	(0.13)
Region Fixed Effects				
Asia		0.43*	0.47*	0.33
		(0.25)	(0.27)	(0.26)
Latin America & Carib.		0.02	-0.17	-0.39
		(0.31)	(0.35)	(0.31)
Middle East & N. Africa		0.44	0.60*	0.62*
		(0.31)	(0.35)	(0.33)
Pacific & Oceania		0.37	0.45	-0.80
		(0.48)	(0.53)	(0.52)
Sub-Saharan Africa		0.94***	0.87***	0.20
		(0.29)	(0.30)	(0.29)
Regime Type Controls				
Democracy			-0.21	-0.12
			(0.41)	(0.38)
Military			0.17	0.09
			(0.41)	(0.38)
Monarchy			-0.60	-0.51
			(0.43)	(0.42)
Communist			0.43	0.23
			(0.56)	(0.49)
One-Party			-0.25	-0.19
			(0.46)	(0.43)
Contextual Controls				
Colony				-0.50
				(0.39)
Urban				-1.59***
				(0.24)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	210	210	210	210
R^2	0.21	0.33	0.36	0.49

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category.

Comments

The results, presented in Tables 5 through 8, provide confirmation of my main hypotheses, even when employing different and arguably less relevant proxies of intensity. Regarding Hypothesis 1, the U-shaped relationship remains robust across specifications, with the turning point consistently located within the central domain of the data. Similarly, for Hypothesis 2, the effect of vanguard competition remains positive and statistically significant regardless of the proxy used. Notably, the coefficient for the Vanguard Competition Index is remarkably stable across the different measures, suggesting that opposition fragmentation drives the intensity of violence independently of conflict duration or maximum participation in an episode.

Across these robustness checks, the control variables display patterns largely consistent with the main results. Geographically, relative to the European baseline, Sub-Saharan Africa and Pacific & Oceania consistently exhibit the highest and most significantly positive coefficients for violence intensity in the intermediate specifications. However, these effects tend to vanish in the full models, indicating that the apparent violence in these regions is largely explained by the prevalence of rural and colonial insurgencies. In contrast, the Middle East & North Africa region displays a consistently higher intensity that survives the inclusion of contextual controls, though the magnitude of the effect is generally smaller.

Institutional controls, instead, show more variation and scarce significance in general; most regime types (Military, One-Party, Communist) are statistically indistinguishable from the baseline. Only Monarchies is associated with lower intensity in one fully specified scenario, at varying confidence levels. Finally, the Urban dummy remains the most robust predictor in the model: regardless of whether intensity is measured as a rate, a total, or a category, urban revolutions are consistently and significantly less lethal than their rural counterparts.

8.3 Sample Sensitivity

Third, I test the sensitivity of my results to the composition of the sample. A potential concern is that the structural drivers of violence in specific subsets of episodes may differ fundamentally from the general population. To address this, I perform two distinct exclusion exercises. First, I re-estimate the baseline specifications after excluding all events taking place in colonies, as the dynamics of colonialism and decolonization may follow a different logic than domestic revolutions. Second, I exclude episodes occurring within democratic regimes. This restriction is crucial to ensure that my findings, particularly the U-shaped relationship with information quality, are not merely the effects of the distinct institutional constraints or high-transparency baselines associated with democracies. In both restricted samples, the coefficients of interest remain robust and statistically significant, confirming that the results are not driven by these specific sub-populations.

Excluding Colonies

Table 9 reports the results for Hypothesis 1, regarding non-colonies ($N = 152$). The U-shaped relationship remains robust and statistically significant. In the fully specified model (Column 4), the linear coefficient is negative ($\beta_1 = -4.73$, $p < 0.05$) and the quadratic coefficient is positive ($\beta_2 = 4.80$, $p < 0.05$). The estimated turning point is 0.49, virtually identical to the baseline estimate. This confirms that the non-monotonic effect of information is not an artifact of decolonization but a robust feature of domestic revolutionary struggles.

Table 9: Robustness H1: Excluding Colonial Episodes

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	-4.15*	-4.02*	-5.69**	-4.73**
	(2.39)	(2.30)	(2.68)	(1.84)
Freedom of Expression Sq. (Q^2)	3.53	4.01*	6.37**	4.80**
	(2.40)	(2.25)	(2.84)	(1.99)
Region Fixed Effects				
Asia		0.97**	1.10***	0.48
		(0.39)	(0.42)	(0.32)
Latin America & Carib.		0.46	0.18	-0.49
		(0.39)	(0.43)	(0.36)
Middle East & N. Africa		1.37**	1.88***	1.10**
		(0.53)	(0.56)	(0.47)
Pacific & Oceania		3.79***	3.23***	0.54
		(0.74)	(0.83)	(0.84)
Sub-Saharan Africa		1.79***	1.94***	0.35
		(0.57)	(0.54)	(0.40)
Regime Type Controls				
Democracy			-1.54**	-0.48
			(0.69)	(0.55)
Military			-0.56	0.00
			(0.70)	(0.52)
Monarchy			-1.57**	-0.77
			(0.64)	(0.54)
Communist			0.81	0.09
			(0.73)	(0.56)
One-Party			-0.98	-0.05
			(0.73)	(0.57)
Contextual Controls				
Urban				-3.04***
				(0.32)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	152	152	152	152
R^2	0.03	0.26	0.35	0.63
Turning Point (Q)	0.59	0.50	0.45	0.49

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category.

Table 10 presents the results for Hypothesis 2. The positive relationship between opposition competition and violence remains robust and statistically significant across all specifications ($\gamma = 0.47$, $p < 0.01$ in the full model). This indicates that the competition mechanism operates just as strongly in non-colonial conflicts.

Table 10: Robustness H2: Excluding Colonial Episodes

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	1.20***	1.03***	0.94***	0.47***
	(0.15)	(0.17)	(0.19)	(0.16)
Region Fixed Effects				
Asia		0.84**	0.89**	0.40
		(0.36)	(0.39)	(0.31)
Latin America & Carib.		0.38	0.11	-0.48
		(0.39)	(0.41)	(0.35)
Middle East & N. Africa		0.97*	1.34**	0.96**
		(0.51)	(0.55)	(0.44)
Pacific & Oceania		2.51***	2.71***	0.48
		(0.72)	(0.78)	(0.72)
Sub-Saharan Africa		1.41***	1.42***	0.18
		(0.51)	(0.49)	(0.38)
Regime Type Controls				
Democracy			-0.86	-0.24
			(0.54)	(0.44)
Military			-0.08	0.22
			(0.66)	(0.51)
Monarchy			-1.26*	-0.75
			(0.64)	(0.55)
Communist			0.53	0.11
			(0.78)	(0.64)
One-Party			-0.48	0.18
			(0.71)	(0.57)
Contextual Controls				
Urban				-2.80***
				(0.34)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	152	152	152	152
R^2	0.23	0.37	0.42	0.63

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category.

Regarding the control variables in this restricted sample, the Middle East & North Africa region consistently exhibits significantly higher violence intensity compared to Europe, retaining significance even in the fully saturated models ($z = 1.10$ in H1, $z = 0.96$ in H2). Again, Sub-Saharan Africa and Pacific & Oceania display large positive coefficients in the intermediate specifications, but these effects are largely absorbed by the contextual controls in the full model. Institutional types show weak patterns in this domestic sample: both Monarchies and Democracies are associated with significantly lower violence levels in the regime-specific specifications (Column 3). However, these effects lose significance in the full model, due to the large and robust negative coefficient on the Urban dummy across all specifications.

Excluding Democracies

Table 11 restricts the sample to authoritarian regimes only ($N = 155$), excluding all episodes that occurred under democratic rule. Within the subsample of autocracies, the U-shaped pattern is robust and statistically significant. In the fully saturated model (Column 4), the coefficients for Freedom of Expression are large and significant ($\beta_1 = -5.41$, $\beta_2 = 5.32$, $p < 0.01$). Crucially, the turning point in this restricted sample is 0.51, which is practically identical to the inflection point found in the main analysis.

Table 11: Robustness H1: Autocracies Only

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	-6.18**	-6.35***	-6.74**	-5.41***
	(2.38)	(2.29)	(2.58)	(1.82)
Freedom of Expression Sq. (Q^2)	6.17**	7.18***	7.30***	5.32***
	(2.61)	(2.55)	(2.67)	(1.94)
Region Fixed Effects				
Asia		0.36	0.47	0.12
		(0.41)	(0.44)	(0.35)
Latin America & Carib.		0.24	0.19	-0.73
		(0.45)	(0.53)	(0.46)
Middle East & N. Africa		0.83*	1.08**	0.89**
		(0.47)	(0.52)	(0.44)
Pacific & Oceania		2.80***	2.89***	0.41
		(0.83)	(0.92)	(0.95)
Sub-Saharan Africa		1.32**	1.56***	0.03
		(0.56)	(0.57)	(0.49)
Regime Type Controls				
Military			0.19	0.13
			(0.72)	(0.53)
Monarchy			-0.36	-0.49
			(0.66)	(0.59)
Communist			0.39	-0.17
			(0.78)	(0.58)
One-Party			-0.26	-0.10
			(0.73)	(0.59)
Comp. Authoritarian			0.19	-0.13
			(0.53)	(0.44)
Contextual Controls				
Colony				-1.29**
				(0.63)
Urban				-2.94***
				(0.31)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	155	155	155	155
R^2	0.05	0.26	0.30	0.59
Turning Point (Q)	0.50	0.44	0.46	0.51

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category.

Table 12 performs the corresponding test for Hypothesis 2. The estimates confirm that the competitive escalation mechanism is structurally robust within autocracies. The coefficient on the Vanguard Competition Index is positive and statistically significant at the 1% level across all specifications. Notably, in the fully saturated model (Column

4), the estimated effect is $\gamma = 0.52$.

Table 12: Robustness H2: Autocracies Only

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	1.18***	1.01***	1.02***	0.52***
	(0.16)	(0.17)	(0.19)	(0.18)
Region Fixed Effects				
Asia		0.34	0.05	0.05
		(0.38)	(0.33)	(0.33)
Latin America & Carib.		0.06	-0.70	-0.70
		(0.49)	(0.44)	(0.44)
Middle East & N. Africa		0.80	0.80*	0.80*
		(0.50)	(0.42)	(0.42)
Pacific & Oceania		2.63***	0.43	0.43
		(0.83)	(0.80)	(0.80)
Sub-Saharan Africa		1.45***	0.07	0.07
		(0.51)	(0.47)	(0.47)
Regime Type Controls				
Military			0.75	0.49
			(0.63)	(0.53)
Monarchy			-0.39	-0.59
			(0.65)	(0.62)
Communist			0.36	0.04
			(0.76)	(0.62)
One-Party			0.03	0.12
			(0.66)	(0.59)
Comp. Authoritarian			-0.02	-0.25
			(0.45)	(0.42)
Contextual Controls				
Colony				-0.88
				(0.60)
Urban				-2.74***
				(0.32)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	159	159	159	159
R^2	0.20	0.34	0.37	0.59

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category.

Regarding the control variables in the restricted autocracy sample, the results largely mirror the patterns observed in the full population. The Urban dummy remains the most powerful and robust predictor of reduced lethality, with coefficients ranging from -2.74 to -2.94 in the full models. Geographically, the Middle East & North Africa region continues to exhibit a positive and statistically significant residual effect), suggesting that authoritarian regimes in this region face structurally higher violence intensity relative to the European baseline, even after accounting for institutional and contextual factors. In contrast, the large positive coefficients initially observed for Sub-Saharan Africa and Pacific & Oceania in the intermediate specifications vanish in the full model, indicating that the high intensity in these regions is fully explained by their lower urbanization rates and colonial histories. Finally, within the universe of autocracies, specific regime subtypes (Military, One-Party, Communist) yield coefficients that are statistically insignificant.

8.4 Outlier Mitigation

Finally, I address the potential influence of extreme observations. Given the high variance in conflict intensity data, there is a risk that the results could be driven by a small number of outlier episodes with exceptionally high or low violence. To mitigate this, I employ Iteratively Reweighted Least Squares (IRLS) robust regression. This method assigns weights to each observation based on the absolute size of its residual, downweighting extreme cases to limit their influence on the estimates.

Table 13 results provide a more cautious but still supportive confirmation of Hypothesis 1. In the specifications controlling for region, decade, and regime type (Columns 2 and 3), the U-shaped relationship is preserved and even intensifies; in Column 3, the coefficients are larger than in the OLS baseline ($\beta_1 = -7.40, \beta_2 = 7.55, p < 0.01$). This confirms that the non-monotonic effect of information is not an artifact of extreme outliers.

However, it is worth looking carefully at what emerges in the full specification of the robust regression (Column 4). Here, the statistical significance of the information variables fades away (despite the persistence of correct signs), and the model fit jumps to an exceptionally high $R^2 = 0.90$. Please note that the R^2 statistics reported for the robust regression specifications are based on the weighted variance of the data. Because the iteratively reweighted least squares (IRLS) algorithm downweights large residuals, effectively removing the observations that the model fails to predict well, the resulting pseudo-R^2 is mechanically higher than in the OLS baseline. This value represents the fit to the "core" data subset rather than the full sample variance and should not be directly compared to the standard OLS R^2. This pattern suggests that the re-weighting algorithm, when presented with the powerful Urban dummy, effectively treats the binary urban-rural distinction as the sole determinant of "normal" observations, down-weighting deviations as outliers until the control variable absorbs nearly all available variation. I argue that this specific result is an overly restrictive test that does not undermine my core findings. The most informative test for robustness against outliers is found in Column 3, which controls for all structural factors (Regime, Region, Decade) except the dominant Urban and Colony indicators.

Table 13: Robustness H1: Sensitivity to Outliers (Robust Regression)

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Freedom of Expression (Q)	0.30	-4.95**	-7.40***	-1.22
	(0.83)	(2.23)	(2.52)	(0.76)
Freedom of Expression Sq. (Q^2)	-0.27	4.55*	7.55***	0.72
	(0.89)	(2.38)	(2.79)	(0.85)
Region Fixed Effects				
Asia		0.35	0.37	0.05
		(0.48)	(0.46)	(0.15)
Latin America & Carib.		0.32	0.44	-0.16
		(0.58)	(0.51)	(0.18)
Middle East & N. Africa		0.95*	0.76	0.13
		(0.57)	(0.51)	(0.17)
Pacific & Oceania		3.41	3.92*	1.42**
		(2.17)	(2.08)	(0.66)
Sub-Saharan Africa		1.30**	1.13**	-0.07
		(0.57)	(0.50)	(0.19)
Regime Type Controls				
Military			-0.17	-0.74***
			(0.67)	(0.22)
Monarchy			-0.41	-0.56**
			(0.73)	(0.24)
Communist			0.60	0.26
			(0.80)	(0.24)
One-Party			-0.49	-0.62***
			(0.69)	(0.23)
Comp. Authoritarian			0.20	-0.58***
			(0.54)	(0.18)
Contextual Controls				
Colony				-1.09***
				(0.22)
Urban				-3.31***
				(0.12)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	173	173	173	173
R^2	0.00	0.21	0.27	0.90
Turning Point (Q)	0.55	0.54	0.49	0.85

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The turning point is calculated as $-\beta_1/2\beta_2$. In Column 2, 3, and 4, Europe is the regional reference category. The R^2 statistics reported for the robust regression specifications are based on the weighted variance of the data. Because the iteratively reweighted least squares (IRLS) algorithm downweights large residuals, effectively removing the observations that the model fails to predict well, the resulting pseudo-R^2 is mechanically higher than in the OLS baseline. This value represents the fit to the "core" data subset rather than the full sample variance and should not be directly compared to the standard OLS R^2.

Table 14 applies the robust regression estimator to the Vanguard Competition hypothesis. The results provide strikingly strong support for the theory. Across all four specifications, the coefficient on the Vanguard Competition Index (G) is positive and statistically significant at the 1% level.

Most notably, in the fully saturated model (Column 4), the effect of opposition fragmentation remains highly significant ($\gamma = 0.23, p < 0.01$) even despite the massive increase in model fit ($R^2 = 0.87$) driven by the re-weighting of the urban variable. Unlike the information variable in the previous table, the signal from vanguard competition is sufficiently distinct from the structural urban-rural divide that it survives the aggressive downweighting of outliers. This confirms that the violence-inducing effect of inter-group rivalry is a pervasive feature of the data, operating consistently across both the "core" of the distribution and the more extreme cases.

Table 14: Robustness: Vanguard Competition (Sensitivity to Outliers)

Dep var: *Yearly Deaths Index*	(1) Baseline	(2) + Region/Decade	(3) + Regime	(4) Full Model
Vanguard Competition Index (G)	1.13***	0.92***	0.86***	0.23***
	(0.17)	(0.20)	(0.21)	(0.08)
Region Fixed Effects				
Asia		0.38	0.33	-0.00
		(0.41)	(0.44)	(0.17)
Latin America & Carib.		0.39	0.26	-0.15
		(0.47)	(0.54)	(0.20)
Middle East & N. Africa		0.64	0.82	0.04
		(0.45)	(0.51)	(0.20)
Pacific & Oceania		2.57	2.84	0.84
		(1.92)	(2.02)	(0.76)
Sub-Saharan Africa		1.22***	1.34**	-0.15
		(0.44)	(0.52)	(0.21)
Regime Type Controls				
Democracy			-0.43	-0.13
			(0.60)	(0.25)
Military			0.25	-0.33
			(0.61)	(0.25)
Monarchy			-0.53	-0.25
			(0.65)	(0.28)
Communist			0.58	0.26
			(0.73)	(0.28)
One-Party			-0.23	-0.22
			(0.62)	(0.27)
Contextual Controls				
Colony				-0.23
				(0.25)
Urban				-3.40***
				(0.15)
Decade Fixed Effects	No	Yes	Yes	Yes
Ruling Situation Controls	No	No	Yes	Yes
Observations	177	177	177	177
R^2	0.20	0.29	0.32	0.87

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In Column 2, 3, and 4, Europe is the regional reference category. The R^2 statistics reported for the robust regression specifications are based on the weighted variance of the data. Because the iteratively reweighted least squares (IRLS) algorithm downweights large residuals, effectively removing the observations that the model fails to predict well, the resulting pseudo-R^2 is mechanically higher than in the OLS baseline. This value represents the fit to the "core" data subset rather than the full sample variance and should not be directly compared to the standard OLS R^2.

In the robust regression specifications, the control variables show different patterns compared to the OLS baselines. Geographically, Pacific & Oceania is a robust predictor of high violence intensity in the information model, though it loses precision in the H2 specification. Conversely, Middle East & North Africa, which consistently predicted higher violence in previous models, loses its statistical significance entirely in the full robust specifications. Institutional controls display a divergence: while several of them are significant negative predictors in the H1 analysis, they become statistically insignificant in the H2 model. This instability suggests that once the influence of outliers is reduced and the dominant Urban dummy is accounted for, the specific institutional architecture of the regime exercises a less consistent effect on conflict intensity.

9 Conclusion

This paper has developed a theoretical framework linking the quality of public information to the intensity of revolt in global games of regime change. The model builds on the standard global games setting, including both private and public information, and extends it by introducing the intensity of revolt as a strategic variable that affects both the effectiveness of collective action and the expected costs of failure. By endogenizing intensity through the interaction of organized vanguard groups and accounting for regime response, the analysis provides a unified investigation of how information precision and group dynamics jointly determine the equilibrium level of conflict intensity.

The theoretical analysis reveals that the precision of public information influences revolt intensity in a non-monotonic way. When the public signal strongly favors the regime, greater precision reduces intensity by discouraging participation; when the signal strongly disfavors the regime, precision increases intensity by facilitating coordination. For intermediate values of the public signal, the relationship follows a U-shaped pattern: moderate precision reduces intensity, but high precision revives it as a tool for coordination. Intensity is high also when information is scarce (serving as a substitute coordination device). These dynamics remain present when the intensity of revolt arises endogenously from the strategic interaction among vanguard groups, and when accounting also for the regime's response to obtain the total intensity of an episode. In the decentralized setting, equilibrium intensity increases with the number of competing vanguard groups contributing to the uprising. When vanguards internalize individual costs, both simultaneous (Cournot-like) and sequential (Stackelberg-like) interactions generate suboptimal intensity relative to the collective optimum, but the competitive pressure of simultaneous interplay pushes the overall equilibrium intensity upward.

I empirically test these predictions using the *Revolutionary Episodes* dataset (1900–2014), drawing 177 episodes from the mass mobilization events combined with historical Freedom of Expression indices. The empirical results provide robust support for the theoretical model. First, I identified a generalized statistically significant U-shaped relationship between information quality and total conflict intensity, with a turning point located approximately at the midpoint of the transparency scale. This confirms the "transparency trap" hypothesis: violence is minimized in semi-transparent environments but escalates under both total suppression and high openness. Such results are supporting the claim that while the theoretical framework identifies this non-monotonicity under specific parameter restrictions, these conditions provide a robust approximation of real world scenarios. Second, I found that fragmentation in the opposition, proxied by the Vanguard Competition Index, structurally escalates conflict intensity. This linear positive effect is consistent with the competition mechanism, confirming that the presence of multiple vanguard groups acts as a multiplier of violence.

The framework and findings clarify the strategic effects of information environments on political stability. Changes in the precision of public signals, interpretable as shifts in media transparency or the credibility of official communication, alter the equilibrium intensity of revolt through their impact on coordination. The results highlight that transparency reforms, media liberalization, or increased availability of public data can have counterintuitive consequences: depending on prior beliefs, they may reduce or amplify the incentives for violent mobilization. By linking informational precision, coordination, and strategic competition among vanguard actors, the paper provides a tractable foundation for studying how communication environments influence the stability of political regimes.

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10 Appendix A

10.1 Computation of Derivatives

Recall the implicitly defined equilibrium couple in the model with both public and private information

$$\begin{cases} x^* = \dfrac{1}{\beta}\left\{\left[\theta^* - \dfrac{1}{\sqrt{\alpha+\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right)\right](\alpha+\beta) - \alpha z\right\} \\ \theta^* = f(v)\cdot\Phi\left(\dfrac{\alpha(\theta^*-z)}{\sqrt{\beta}} - \sqrt{\dfrac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\dfrac{c+g(v)}{1+g(v)}\right)\right). \end{cases}$$

Now, let us compute $\frac{\partial x^*}{\partial v}$. Start from the first equation defining the equilibrium couple, considering θ^* as a function on v. It results

$$\frac{\partial x^*}{\partial v} = \frac{\sqrt{\alpha+\beta}(-1+c)g'(v)}{\beta(1+g(v))^2}\Phi^{-1\prime}\left(\frac{c+g(v)}{1+g(v)}\right) + \frac{\alpha+\beta}{\beta}\frac{\partial\theta^*}{\partial v}.$$

Then, from the second equation, the implicit derivative can be obtained

$$\begin{aligned}\frac{\partial\theta^*}{\partial v} = {} & \frac{\sqrt{\beta}}{(1+g(v))^2\left(\sqrt{\beta} - \alpha f(v)\Phi'\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}} - \sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right)} \\ & \times\left[(1+g(v))^2 f'(v)\Phi\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}} - \sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right. \\ & + \sqrt{\frac{\alpha+\beta}{\beta}}(-1+c)f(v)g'(v)\Phi^{-1\prime}\left(\frac{c+g(v)}{1+g(v)}\right) \\ & \left.\times\Phi'\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}} - \sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right].\end{aligned}$$

At this point, it is possible to combine the two expressions above to obtain

$$
\begin{aligned}
\frac{\partial x^*}{\partial v} &= \frac{1}{\beta}\left(\frac{\sqrt{\alpha+\beta}(-1+c)g'(v)}{(1+g(v))^2}\Phi^{-1\prime}\left(\frac{c+g(v)}{1+g(v)}\right)\right. \\
&+(\alpha+\beta)\frac{\sqrt{\beta}}{(1+g(v))^2\left(\sqrt{\beta}-\alpha f(v)\Phi'\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}}-\sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right)} \\
&\times\left[(1+g(v))^2 f'(v)\Phi\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}}-\sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right. \\
&+\sqrt{\frac{\alpha+\beta}{\beta}}(-1+c)f(v)g'(v)\Phi^{-1\prime}\left(\frac{c+g(v)}{1+g(v)}\right) \\
&\left.\left.\times\Phi'\left(\frac{\alpha(\theta^*-z)}{\sqrt{\beta}}-\sqrt{\frac{\alpha+\beta}{\beta}}\Phi^{-1}\left(\frac{c+g(v)}{1+g(v)}\right)\right)\right]\right).
\end{aligned}
$$

Recalling that $\Phi^{-1\prime}(y) = \frac{1}{\phi(\Phi^{-1}(y))}$, the sign of this derivative is ambiguous, allowing for the existence of critical points.

10.2 Polynomial Approximations

To better understand the structural properties of certain key curves resulting from the models, it could be useful to construct polynomial approximations. These approximations (possibly at higher degrees) facilitate analytical tractability and allow us to study features such as curvature, inflection points, and comparative statics more systematically, if needed. In what follows, I provide two illustrative examples, focusing on the participation threshold curves, which play a central role in determining agents' entry decisions.

Let us start with the simplest model with private information only.

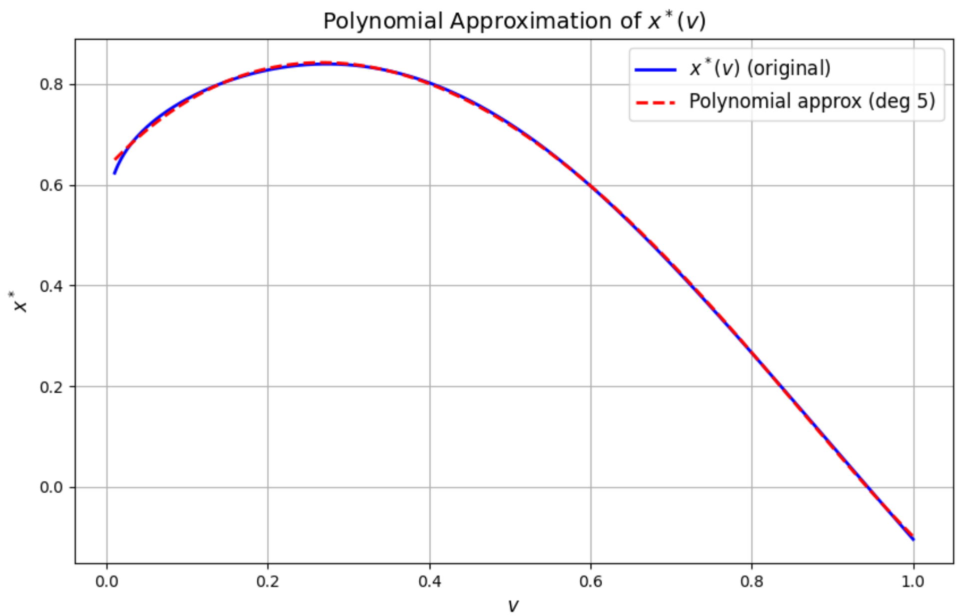

Figure 22: Polynomial approximation, model with private information.

```
Polynomial expression:
       5         4         3         2
1.635 x - 3.586 x + 3.838 x - 4.356 x + 1.737 x + 0.6324
```

And now let us see the more complex scenario with both public and private information.

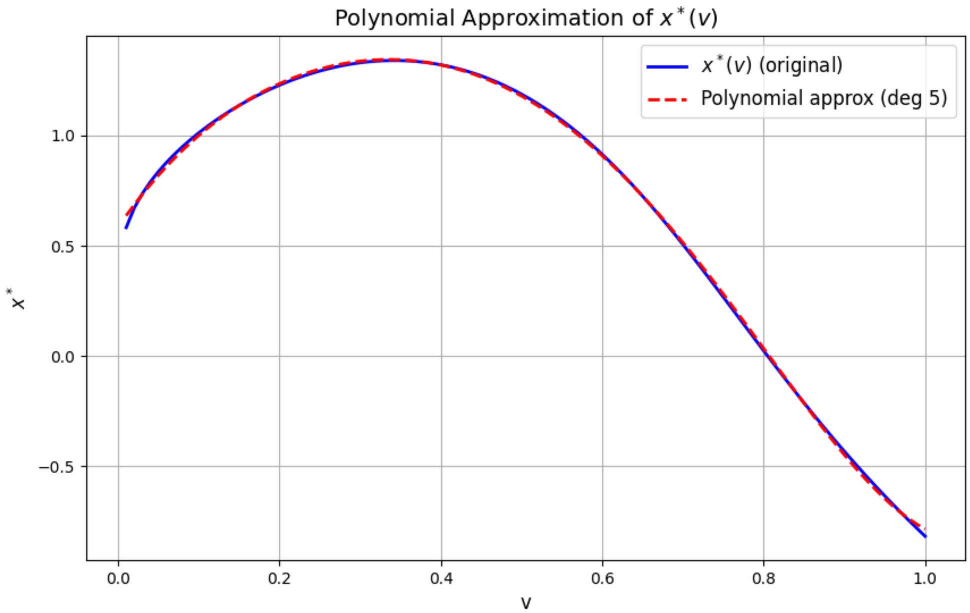

Figure 23: Polynomial approximation, model with private and public information.

```
Polynomial expression:
       5          4          3          2
13.55 x - 28.03 x + 21.55 x - 13.78 x + 5.35 x + 0.5839
```

If necessary, the polynomial approximation of more curves can be easily obtained employing the same method.

11 Appendix B

11.1 Explorative Visualizations

This section provides exploratory visualizations of the main variables and structural controls used in the analysis.

Bivariate Relationships

Figures 24 and 25 visualize the raw bivariate relationships corresponding to my two central hypotheses. Figure 24 fits a quadratic curve to the relationship between information quality and total violence intensity. The plot suggests the possible existence of the U-shaped pattern, where intensity is minimized at intermediate levels of transparency.

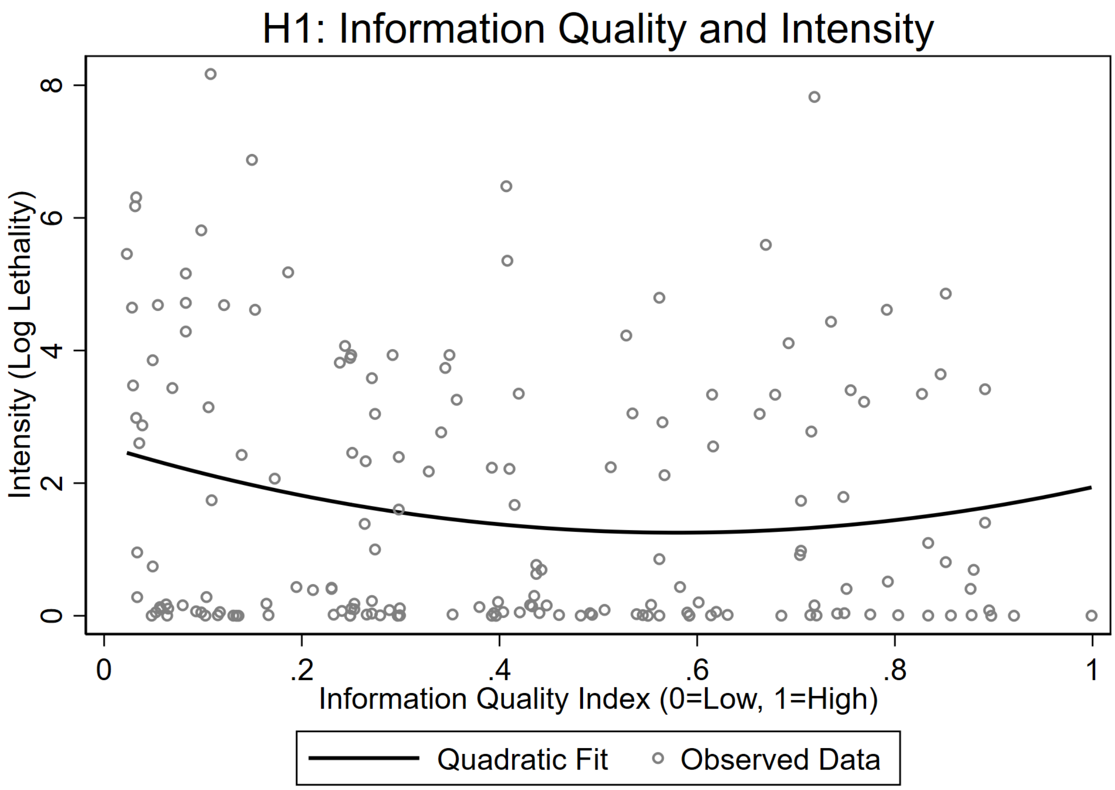

Figure 24: H1: Information Quality vs. Violence Intensity

Figure 25 fits a linear regression line to the relationship between the Vanguard Competition Index and total violence intensity. The upward slope highlights the positive correlation predicted by the outbidding mechanism.

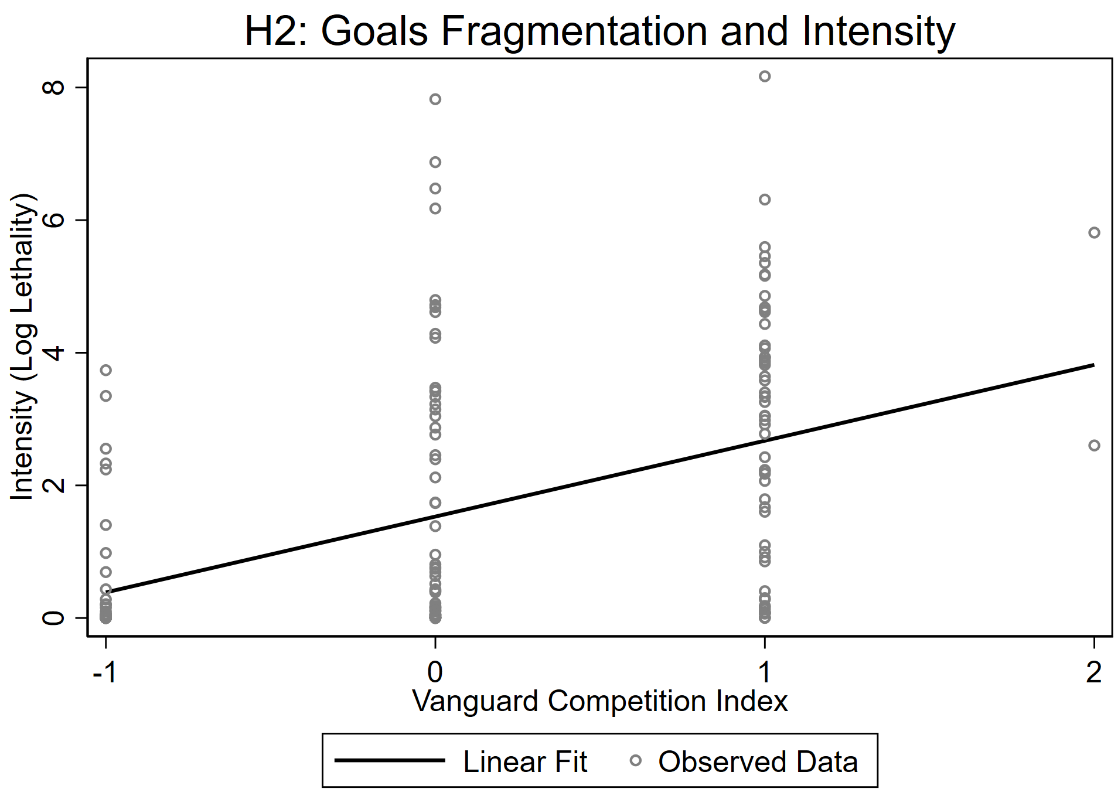

Figure 25: H2: Vanguard Competition vs. Violence Intensity

Structural Variation

Figures 26 through 30 justify the inclusion of structural and contextual fixed effects. Figure 26 highlights significant regional heterogeneity. The bar chart shows that revolutionary episodes have heterogeneous violence across regions.

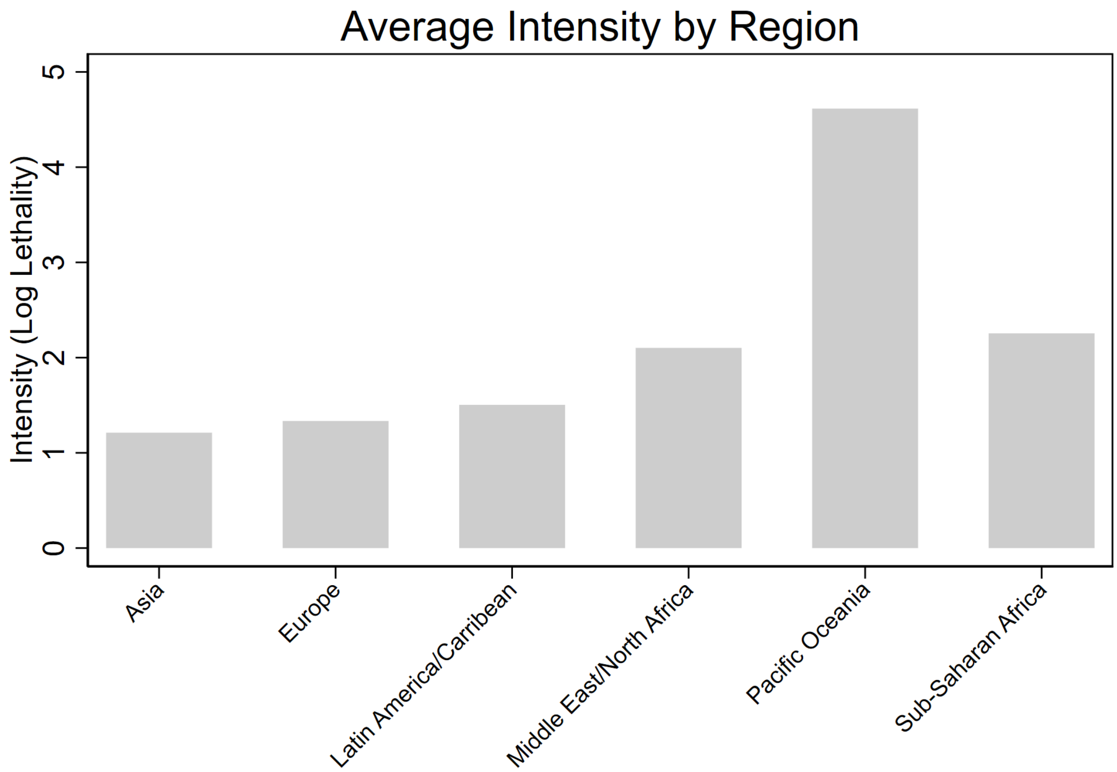

Figure 26: Average Intensity by Region

Similarly, Figure 27 demonstrates variation across institutional frameworks. The observable differences in average total intensity between varying regime types support the inclusion of regime type controls to account for institutional constraints on violence.

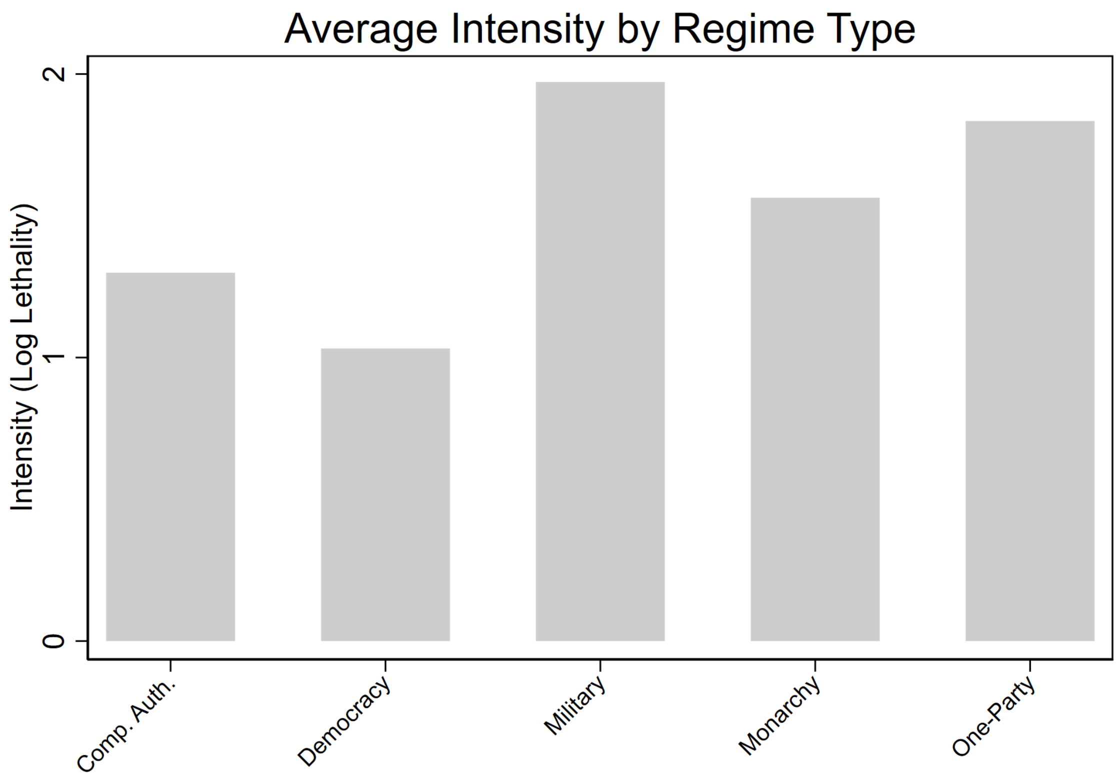

Figure 27: Average Intensity by Regime Type

Figure 28 reveals non-linear temporal trends. Violence intensity varies across decades, validating the use of decade fixed effects to account for global waves of instability.

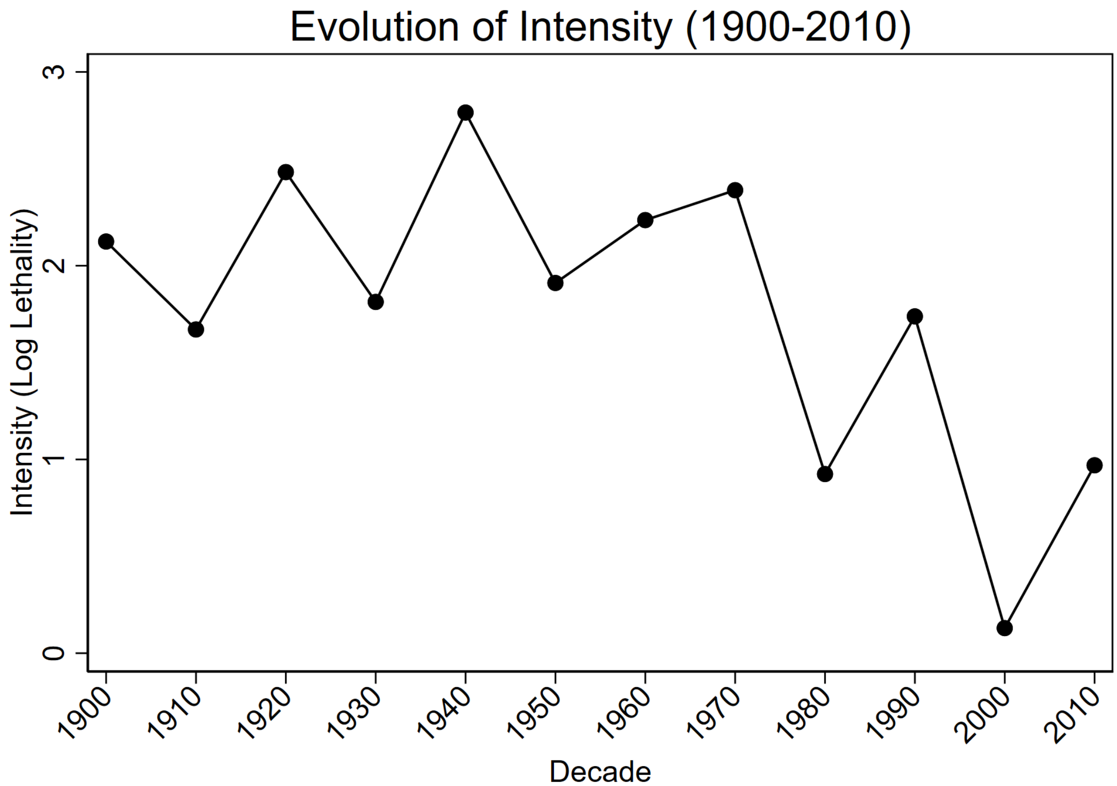

Figure 28: Temporal Trends in Violence Intensity (1900–2010)

Finally, Figures 29 and 30 display differences in intensity based on urbanization and colonial status, validating their inclusion as contextual controls.

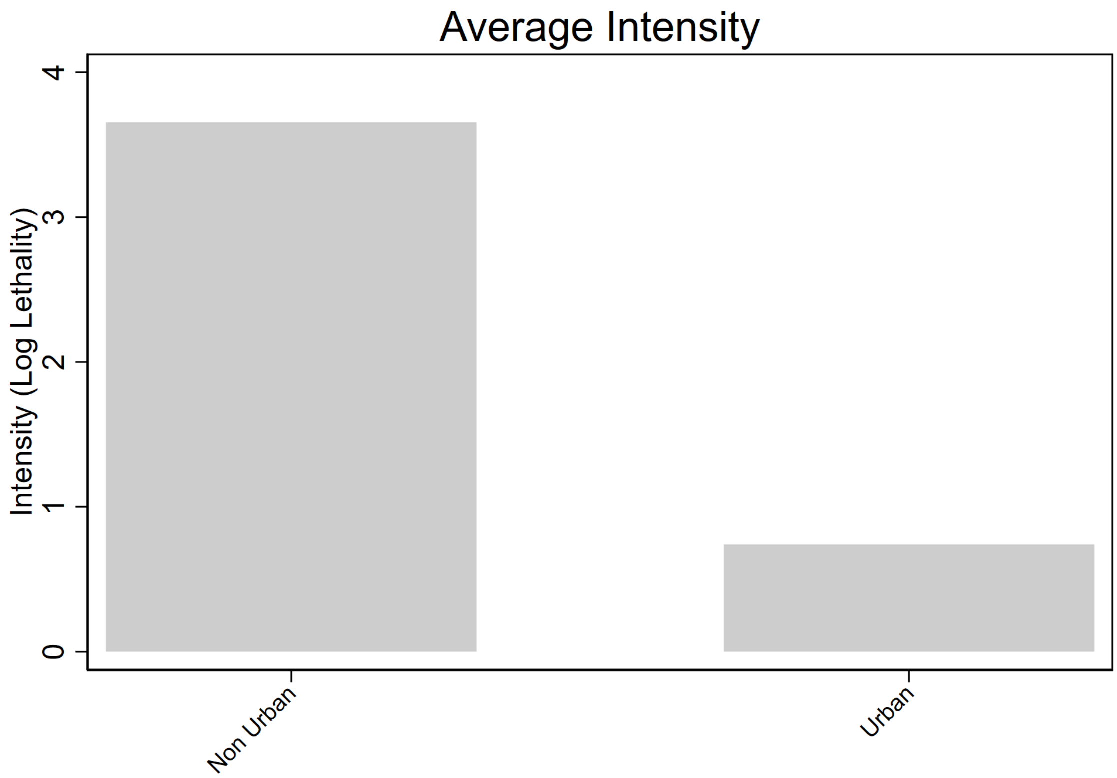

Figure 29: Average Intensity by Urban Status

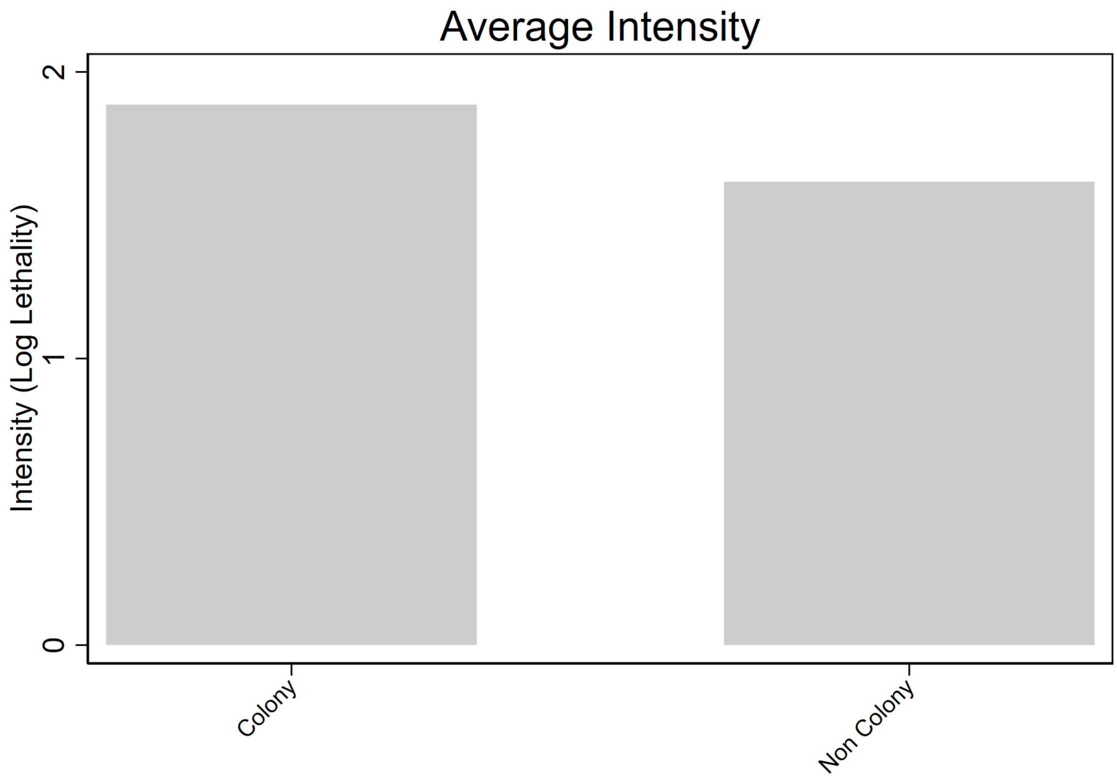

Figure 30: Average Intensity by Colonial Status

11.2 Visualizations with Full Controls

This subsection provides visualizations of the main results derived from the fully specified regression models. Figures 31 and 32 illustrate the estimated relationship between the main independent variables and total violence intensity, based on the full models (Column 4) which control for decade, region, and regime type.

Figure 31 confirms the U-shaped relationship: predicted violence is highest at the extremes of the information spectrum and significantly lower at intermediate levels, especially after accounting for structural controls.

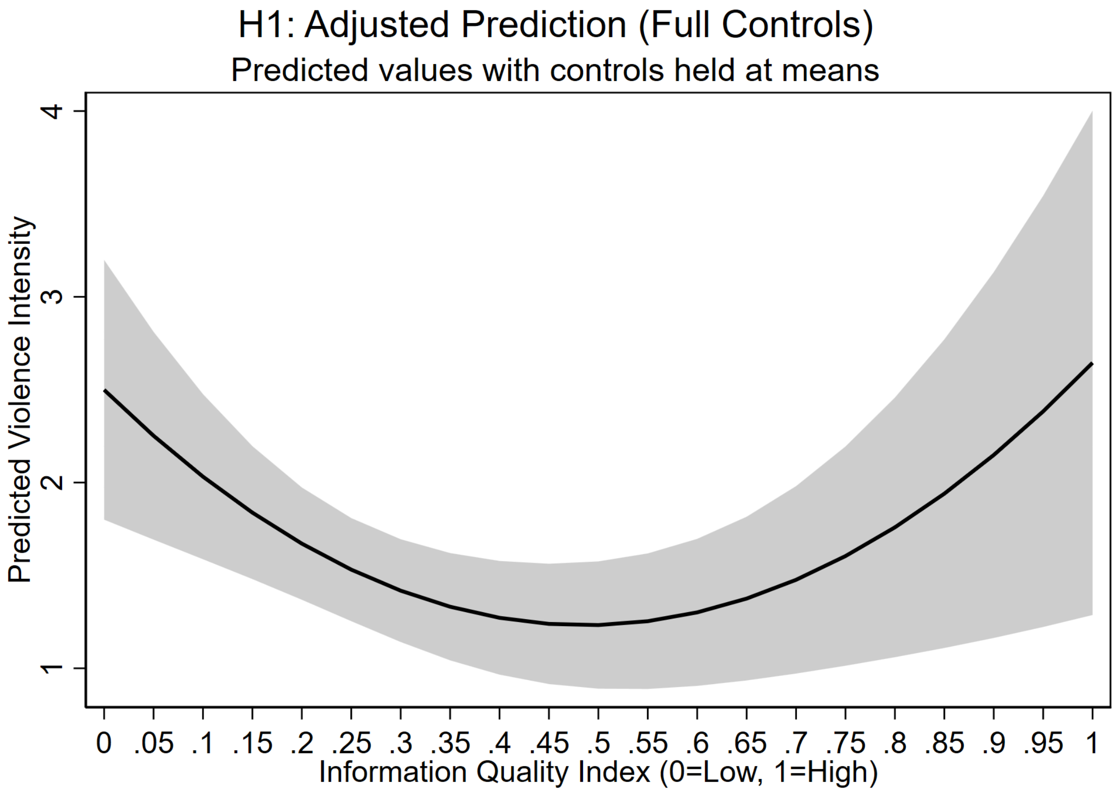

Figure 31: H1: Adjusted Prediction of Violence by Information Quality

Notes: The solid line represents the predicted violence intensity based on the full OLS model, holding all control variables at their means. The shaded grey area represents the 95% confidence interval.

Figure 32 confirms the positive linear relationship: as the number of Vanguard Competition Index proxying vanguard groups increases, the predicted intensity of violence rises significantly, consistent with the hypothesis.

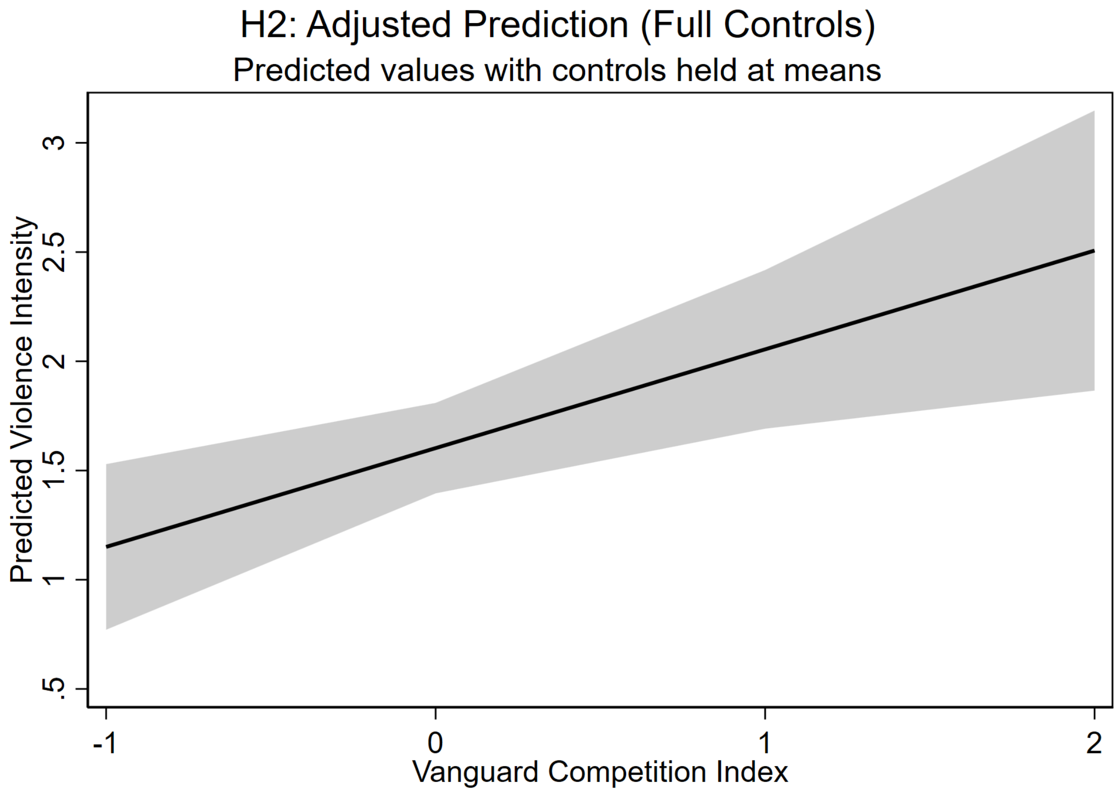

Figure 32: H2: Adjusted Prediction of Violence by Vanguard Competition

Notes: The solid line represents the predicted violence intensity based on the full OLS model, holding all control variables at their means. The shaded grey area represents the 95% confidence interval.