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Keywords
Political Revolutions, Arab Spring, Agent-Based Models

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Understanding the Dynamics of Violent Political Revolutions in an Agent-Based Framework

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December 6, 2014

Abstract

This paper develops an agent-based computational model of violent political revolution in which a subjugated population of agents and an armed revolutionary organization try to overthrow a central authority and its loyal forces. The model replicates several patterns of rebellion consistent with the major historical revolutions and provides an explanation for the multiplicity of outcomes that can arise from an uprising. This last point is of particular interest if we consider the heterogeneity of political outcomes produced by the recent revolutionary episodes in the so-called Arab Spring.

1 Introduction

After the recent wave of political revolutions in the Arab World, the phenomenon of political revolutions has attracted again the attention of researchers. In particular, this paper presents an agent-based computational model that describes the common dynamics of the major political revolutions and replicates some stylized facts.

In the model there are three types of actors interacting in a bi-dimensional torus space: a population of agents oppressed by a central government, the members of a revolutionary organization that tries to overthrow the government through an armed uprising, and, finally, the loyal cops who have the task to suppress any kind of rebellion.

This simple model is able to reproduce several patterns of rebellion consistent with the major historical revolutions: a pre-revolutionary period characterized by spontaneous riots, motivated mainly by poor economic conditions and social inequality, is followed by a proper revolutionary rebellion, in which organized elements mobilize popular masses against the central government.

Moreover, the model provides an explanation for the multiplicity of outcomes that can arise from an uprising: a completely successful revolution in which the

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central authority is overthrown; an unsuccessful rebellion followed by the return to the status quo; an intermediate case, in which the uprising is not able to change the political system but it is strong enough to destabilize the country and push it toward anarchy.

The heterogeneity of scenarios predicted by the model is of particular interest if we consider the recent experience provided by the Arab Spring, in which many rebellions, started in a quite similar way, ended up with completely different political outcomes: e.g., the successful revolution in Tunisia, the unsuccessful protests in Saudi Arabia and the civil war in Syria.

Before entering into the model details, the economic literature about revolutions and the feedbacks with the other social sciences, in particular with the political science theories of revolution, are briefly summarized.

For decades, the most popular theories of revolution were the Marxian theory and the relative deprivation theory: the former emphasizes the role of changes in production methods in generating discontent and rebellion while the latter focuses on the gap between economic expectations and realized economic performances to explain the sense of frustration and, consequently, the riot participation. Both of them establish an automatic link between the structural conditions that generate grievance in the society and the likelihood of revolutionary episodes. Moreover, in both theories, the participation in revolutionary episodes is motivated by a collective good argument, such as the desire to change the oppressive social order. Two of the most influential scholars in this stream of literature are Slaeepol (1979) for the Marxian theory and Davies (1962) for the relative deprivation theory.

By contrast, Tullock (1971) develops an economic approach to explain the participation in revolutions: since the benefit of an extra unit of public good is small relative to the cost of obtaining it through the participation in a rebellion, individuals decide to participate or not according to their private gains or losses. Silver (1974) provides a classification of revolutions based on Tullock’s theory. Moreover, Kuran (1992, 1991, 1995) criticizes the idea of an automatic relationship between social grievance and revolution, arguing that most historical revolutions were unanticipated. He provides an explanation based on the observation that people who dislike their government tend to conceal their political preferences as long as the opposition seems weak. For this reasons, regimes that appear absolutely stable might see their support vanished immediately after a slight surge in the opposition’s size, even if caused by insignificant events.

Afterwards, the economic and the political science literature have tried to find a solution to the collective action problems inherent in revolutions. For example, criticizing Tullock’s view, Lichbach (1994, 1995, 1996) identifies some solutions based on sanctioning, and group identification methods: these solutions include the possibility of imposing community obligations, establishing institutional mechanisms, arranging contracts and using authority. For an example of an institutional kind of solution in the context of 18th-century merchant sailors see Leeson (2010).

Furthermore, in line with Kuran’s theory, Rubin (2014) argues that cascades of preference revelation are more likely to happen after a big shock in highly
centralized regimes because in these political systems citizens have higher incentives to falsify their true political opinions in order to avoid economic or legal sanctions imposed by the central authority. Makowsky and Rubin (2013) develop also an agent-based model to study how social network technology favours preference revelation in centralized societies.

There are also some game theoretic papers that analyse the economic causes of political change: for instance, following Acemoglu and Robinson's (2001) model of the economic origins of democracy, Ellis and Fender (2011) derive conditions under which democracy arises peacefully, when it occurs after a revolution and when oligarchic governments persist.

Finally, this paper is also greatly influenced by Granovetter’s (1978) theory about threshold models of collective behaviours and by Epstein’s (2002) agent-based model of civil violence. According to Granovetter, individuals face many situations with multiple alternatives and the costs and benefits associated to the different alternatives depend on how many other individuals have chosen which alternative. For this reason, each individual has a personal threshold and decides to join a collective action, like a riot or a strike, if the number of people who already participate exceeds this threshold. Following this idea, Epstein develops an agent-based model of civil violence in which agents decide to rebel against the government if their level of grievance corrected by the risk of being arrested is higher than their personal threshold.

The rest of the paper is organized as follows: next section describes the model; Section 3 presents the three outcomes generated by the model as well as their dependence to the model parameters using many simulations; in Section 4 some statistical models are estimated in order to analyse the main features of the simulated data; finally, Section 5 concludes.

\section{The Model}

In the agent-based computational model presented in this paper there are three types of players that interact in a bi-dimensional torus space: agents, cops and revolutionaries. Agents are members of a population subjugated to a central authority and they decide to rebel or not against the central authority according to their level of economic and political grievance. Revolutionaries are members of an organized opposition group that seeks to overthrow the central government with an armed uprising. Finally, cops are the forces loyal to the central authority and have the task to suppress any kind of revolt by arresting the active agents and killing the revolutionaries.

In this paragraph, the features of each actor are described in details starting from the agent specification. As in Epstein (2002) the agents’ grievance is the product of an index of economic hardship $H$ and a measure of government illegitimacy, defined as $1 - l$, where $l$ is a parameter measuring the legitimacy of the central authority. In formula:

$$G(y) = (1 - l)H(y)$$

(1)
The difference with respect to Epstein’s specification is that the perceived hardship, and consequently the grievance, is a function of agents’ income \( y \). In fact, each agent is endowed with an income drawn from a normal distribution:
\[
y \sim N(a, b^2)
\]  
(2)

The functional form chosen for the hardship index is:
\[
H(y) = \frac{\exp[-k_1(y - \bar{y})]}{1 + \exp[-k_1(y - \bar{y})]}
\]  
(3)

This function allows to map each agent’s economic condition to a value on the \([0, 1]\) interval. This index is a logistic transformation of the difference between agents’ income and the average income in the population \( \bar{y} \), while \( k_1 \) is simply a positive scale parameter. This expression is similar to the definition of grievance employed by Kim and Hanneman (2011).\(^1\) The social grievance represents the motivation that potentially leads agents to revolt.

On the other hand, the costs of participating in a rebellion are defined as the product of the estimated probability of being arrested \( P \) and the opportunity cost of joining a revolt \( J \):
\[
N(y) = PJ(y)
\]  
(4)

In fact, each agent estimates an arrest probability before actively joining a rebellion. This estimated probability is defined as in Epstein (2002): it is an increasing function of the ratio of cops to already rebellious players inside the vision radius of the agent. In particular, in this model the rebel players can be either the active agents and the revolutionaries:
\[
P = 1 - \exp\left[-k_2 \left( \frac{C_v}{1 + A_v + R_v} \right) \right]
\]  
(5)

Where \( C_v, A_v \) and \( R_v \) represent, respectively, the number of cops, active agents and revolutionaries in action within the agent’s vision. The vision is a circular neighbourhood with centre in the agent’s position and radius equal to \( v \) and it represents the number of lattice positions that an agent is able to inspect. The one in the previous formula makes explicit the fact that an agent, before participating in a riot, counts himself as an active agent: in this way the ratio is always well defined.\(^2\)

If an active agent is arrested by cops, he is forced to stay in jail for a number of periods that is drawn from a uniform distribution on the interval \([0, J_{\max}]\). For this reason, the opportunity cost of rebelling is defined as a function of the

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\(^1\)One of the differences is that the two authors use a local measure of inequality, i.e., the distance of each agent’s wage with respect to the average wage in the agent’s neighbourhood. By contrast, in this model a global measure of inequality is preferred because it should be easier in modern societies to find information about average per capita income in the country rather than the average income of one’s neighbours.

\(^2\)In practice, the floor operator is applied to the ratio of cops to rebel players as in Wilesky’s (2004) version of Epstein’s model.
expected number of periods in jail \( \left( \frac{j_{\text{max}}}{2} \right) \) multiplied by the income the agent loses during the period in jail:

\[
J(y) = k_3 \left\{ \frac{\exp \left[ k_4 \left( y \frac{j_{\text{max}}}{2} \right) \right]}{1 + \exp \left[ k_4 \left( y \frac{j_{\text{max}}}{2} \right) \right]} \right\} - k_5
\]  

(6)

Once again, since the vast majority of the income realizations are positive, the three constants in the last expression are chosen in order to have a transformed logistic function that maps most of the income realizations to a value on the \([0, 1]\) interval. Expression (6) is also consistent with the political violence literature that finds a negative relationship between income and participation in civil violence phenomena. For example, Collier and Hoefler (1998, 2004) and Fearon and Laitin (2003), using cross-country regressions, find that economic growth and income per capita correlate negatively with the risk of civil conflict while Miguel, Satyanath and Sergenti (2004) find a causal negative effect between positive income shocks and civil war incidence in Sub-Saharan African countries employing an instrumental variable approach.

Having defined both the incentives and the costs underlying the participation in riot activities, it is possible to specify the agents’ rule of activation. In particular, agents become active if the difference between the social grievance and the expected opportunity cost of joining a riot exceeds a fixed threshold; otherwise, they remain quiet:

Rule A: if \( G(y) - N(y) > f \) be active; otherwise, be quiet.

Like in Epstein (2002), it is possible to interpret this inequality using Kuran’s (1989) theory: the left hand side represents the expected utility of expressing in public the opposition against the central authority while the right hand side is the utility of falsifying the private political preferences.

The revolutionaries’ behaviour is simpler. Revolutionaries are members of an organized group that try to overthrow the government through an armed conflict. It is possible to interpret this kind of players as a proper revolutionary group or as defected elements from the military that decide to side with the population in revolt. Historical examples of the first type of organizations are the Bourgeois Militia of Paris in the French Revolution (1789), the Bolsheviks and the Red Guards in the Russian Revolution (1917), the leftist revolutionaries of the Organization of Iranian People’s Fedai Guerrillas in the Iranian Revolution (1979), the Muslim Brotherhood in the Egyptian Revolution (2011), the jihadist group of the Islamic State of Iraq and the Levant (ISIS) in the Syrian Civil War (2011), and many others. On the other hand, defections from the military are very common in all revolutions: a typical example could be represented by the pro-Khomeini members of the Iranian Air Force that fought against the loyal Immortal Guards during the 1979 uprisings.

It is assumed that revolutionaries behave according to the following rule:
Rule R: if \( \frac{R_A}{C} > n \) be in action and kill a randomly selected cop inside the vision radius \( v \) with a probability equal to \( r \); otherwise, be quiet.

Where \( R \), \( A \) and \( C \) are the total number of revolutionaries, the total number of active agents and the total number of cops, respectively. Rule R means that revolutionaries decide to enter in action when the ratio of rebel forces to government loyal cops exceeds a given threshold \( n \). In this respect, revolutionaries are different from agents: agents choose their behaviour according to the local information available within their vision radius. On the contrary, revolutionaries act on the basis of a global information because they decide when to start the revolution employing a threshold-based rule that involves the total number of active agents in the population.\(^3\)

When a revolutionary is in action, he kills a randomly selected cop in his vision radius with a probability equal to \( r \). Otherwise, when the ratio is less than the fixed threshold, all revolutionaries remain hidden among the quiet population members and it is not possible for cops to identify them.

Finally, the cops’ behaviour must be described. They simply inspect the lattice positions inside their vision radius and choose at random an active agent or a revolutionary in action: if the randomly selected player is an agent, cops arrest him while they kill him if he is a revolutionary in action with a probability equal to \( c \). Therefore, the cops’ rule is the following:

Rule C: select at random one player among the active agents and the revolutionaries in action within the vision radius \( v \). If the randomly selected player is an agent, arrest him; if he is a revolutionary, kill him with a probability equal to \( c \).

The same vision radius \( v \) is assumed for agents, revolutionaries and cops. Furthermore, it is also possible to interpret the two parameters \( r \) and \( c \) in terms of weapon precision or, more broadly, in terms of effectiveness in the military capacity of the two sides in conflict.

Finally, agents who are not in jail and revolutionaries and cops who are not killed can move to a random site in the lattice space following this simple rule:

Rule M: move to a random site within your vision radius.

To begin each run of the model, the user selects the values for the fixed parameters and the initial densities for the three types of players (see Table 1 for the chosen values). The random values are drawn from the respective distributions and the different actors are randomly situated on the lattice. Then, a player is selected at random, under rule M he moves to a random position within his vision, where he acts according to rule A if he is an agent, rule R if he is a revolutionary or rule C if he is a cop. The model replicates this procedure until the user quits.\(^4\)

\(^3\)It is reasonably assumed that the revolutionary organization is spread over the country and for this reason it is able to obtain a quite precise idea of the total number of active agents in the population.

\(^4\)The model has been implemented using NetLogo [Wilensky(1999)]. The simulated data


| Parameter        | Value | Parameter | Value |
|------------------|-------|-----------|-------|
| Agent Density    | 70%   | c         | 0.7   |
| Revolutionary Density | 3% | r         | 0.3   |
| Cop Density      | 4%    | j_{\text{max}} | 30    |
| Lattice Dimension | 40x40 | v         | 7     |
| l                | 0.85  | k_1       | 1     |
| a                | 4     | k_2       | 2.3   |
| b                | 1     | k_3       | 2     |
| f                | 0.1   | k_4       | 0.05  |
| n                | 1.2   | k_5       | 1     |

Table 1: Base values of the parameters.

3 Model Results

This simple model is able to generate three possible outcomes: a successful revolution in which all cops are killed by revolutionaries and the central government is thus overthrown; an unsuccessful revolution followed by a state of anarchy due to an high number of killed cops; finally, a completely unsuccessful revolution with very few killed cops, which means the return to the status quo after the uprising.

Figure 1 shows these possible outcomes with three simulations. All these three simulations start with a period of instability characterized by small revolts in which the poorest component of the population, formed by those agents with an higher level of grievance and a lower opportunity cost, decides to rebel. But these riots are too small and, therefore, they do not degenerate in revolution. This politically unstable pre-revolutionary period is a common feature of many historical revolutions, e.g., the strikes and workers demonstrations in Russia (1917), in Iran (1977-1978) and in the Arab World (2011), mainly motivated by bad economic conditions, like low wages, high inflation (especially high food prices), inequality, unemployment, and also by low political legitimacy, due to defeat in war for the Tsar in Russia or to the Shah’s unpopular westernized costumes in the case of Iran. Around time 200 a bigger riot happens and the revolutionaries’ threshold rule is satisfied: this implies that revolutionaries come into action and the rebellion, started as a riot motivated by the bad economic conditions of the poorest agents, has now the features of a political revolution. When revolutionaries become active, the agents’ estimated arrest probability goes down and this leads to the huge peak formed by active agents. Moreover, this effect is reinforced by the fact that revolutionaries start to kill cops lowering again the probability of arrest. What happens next depends on the parameters regulating the relative strength of the two factions.

In the upper graph (c = 0.7 and r = 0.3), after the revolutionaries’ activation, a great number of agents become active and for cops is easier to find

employed in the next sections have been generated using the BehaviorSpace tool presented in Netlogo while the statistical analysis has been performed using R [R Core Team (2014)].
Figure 1: Different model scenarios.
active agents than revolutionaries in action: this explains why, after the big peak, a lot of agents are arrested and only few revolutionaries are killed. Hidden among active agents, revolutionaries shoot against cops. When many cops are killed, the number of active agents starts to increase again and when all cops are killed it reaches its maximum, i.e., all the agents with a grievance higher than the threshold become active: the revolution is complete and the government is overthrown. Political scientists have observed one common feature in all successful revolutions: i.e., they occur only when there is some linkage between mass mobilization and the revolutionary movements that place themselves at the head of popular revolts, giving them organization and coherence. This happened with the Bolsheviks and the workers’ riots in 1917 or with the Ayatollah Khomeini and the protests in the bazaars of Iran.\footnote{For a review of the political science literature about revolutions and, in particular, for the role played by revolutionary elites in revolutions see Goldstone (2001, pp. 146-152).} The model is able to capture this link between popular spontaneous riots and organized actions of revolutionaries. Examples of successful rebellions are represented by the three major historical revolutions in France (1789), Russia (1917) and Iran (1979) but also by the recent uprisings in Tunisia, Egypt and Yemen (2011). In all these cases the pre-revolutionary government is overthrown and a new order is established.

Instead, in the middle graph \( (c = 0.6 \text{ and } r = 0.2) \), after the big peak, the armed conflict between revolutionaries and cops is won by the latter side. Nevertheless, a great number of cops remains killed and the revolution is followed by a period of huge, never-ended turmoil: the big reduction of the state’s legal capacity caused by the uprising leads the country toward anarchy. A similar anarchic post-revolutionary situation usually follows a rebellion when the percentage of killed cops exceeds 30%. The anarchic outcome looks like the present civil war scenarios in Syria and Libya, where the 2011 insurrections completely destabilized the two countries, reducing their state capacities.

Finally, in the lower graph \( (c = 0.9 \text{ and } r = 0.1) \), the difference in the military effectiveness of the two factions is too large and only few cops are killed during the uprising (usually less than 30%). This means that after the big rebellion the situation is similar to the pre-revolutionary period: the status quo is maintained. Here the analogy is with the 2011 riots in Saudi Arabia and Bahrain, where the opposition groups were very weak from a military perspective and only few cops were killed in the street violence episodes.

One of the main features shared by many revolutions in history is that they were not anticipated. This pattern has been observed for the first time by Kuran (1989, 1991, 1995) in the dynamics of the French, Russian and Iranian revolutions and in the fall of communist regimes in Eastern Europe.

The model presented in this paper is able to explain why this happens. In fact, figure 2 shows three simulations identical with respect to all the parameters of the model but different in the random components. As it is easy to observe, in the first graph the revolution occurs around time 20, in the second graph it happens around time 90 and, finally, in the third graph the revolution starts
Figure 2: The unpredictability of revolutions.
around time 200. This happens because the riot involving a number of active agents such that it degenerates in revolution is a totally random event, it is a shock that is not possible to anticipate with certainty. This behaviour of the model mimics the real revolutionary events in which the opposition elites or the defected military officers and most of the people that want to rebel against the government have incentives to hide their true fillings until the crucial moment arises and it is not possible to know which episode will lead to mass, rather than local, mobilization.\textsuperscript{6}

In order to explore how the different outcomes of the model vary with the parameters associated to the precision of cops and revolutionaries and with the threshold revolutionaries employ in their decision rule, the graphs contained in figure 3 may be useful. Each graph corresponds to a different threshold rule: in particular, four values are chosen for \(n \in \{0.8, 1.2, 1.4\}\). Then, a grid is constructed with different values for the precision parameters: \(c \in \{0.1, 0.15, 0.20, \ldots, 0.8, 0.85, 0.9\}\) and \(r \in \{0.1, 0.15, 0.20, \ldots, 0.5, 0.55, 0.6\}\).\textsuperscript{7} Finally, for each combination of parameters the simulation is replicated for 10 times and the average of the fraction of killed cops is calculated.

The blue regions in the graphs represent the cases in which a return to the status quo arises after the uprising. In fact, these areas correspond to an extreme high value for the cops’ precision and a very low value for the one of revolutionaries. As \(r\) increases or \(c\) decreases, the outcome of the simulations changes toward anarchy: these outcomes are represented by the lighter blue and white areas in the four graphs. Above a certain level for the two precision parameters, the situation changes from anarchy to successful revolution: the regions of successful revolutions are coloured in violet.

One common feature of the four graphs is that the blue area is far below the 45 degree line: this means that cops need a very high level of precision compared to that one of revolutionaries in order to win the armed conflict. This is due to the strong advantage of revolutionaries: in fact, they can hide themselves among active agents and attack when the government forces are engaged in public order maintenance. This advantage results from the fact that cops extract at random one player from the set of active agents and revolutionaries in action within their vision radius (see rule C) and not from the set formed by revolutionaries alone. This part of the model offers an incentive for revolutionaries to come into action only when spontaneous riots exceed a minimum threshold and contributes to explain why in history revolutionary movements turn active after strikes, protests and riots.

The revolutionaries’ advantage explains also why the dark blue area is smaller in the graph with \(n = 1.2\) compared to the graphs with \(n = 0.8\) or \(n = 1.1\): with the last two thresholds, revolutionaries enter in action too early and are thus exposed to the fire of cops. On the other hand, a threshold rule based on \(n = 1.5\) may lead to a situation without uprisings because there may not be a riot with

\textsuperscript{6}See Goldstone (2001), p. 11 for an application of this concept to the recent uprisings in the Arab World.

\textsuperscript{7}The graphs in figure 3 are cut above the value 0.4 for \(r\) because, in correspondence to higher values of the revolutionaries’ precision, successful revolutions are always observed.
Figure 3: Average fraction of killed cops for different values of the parameters.
Figure 4: Variability of the fraction of killed cops for different values of the parameters.

... a number of active agents such that the revolutionaries’ rule is satisfied or this riot may happen with a very long waiting time: this is exactly what happens in one of the ten simulations and it explains why in the last graph there are not regions in which the ten simulations end up with an average of 100% killed cops. Therefore, among these four thresholds, the best one seems n = 1.2, but this point will be reconsidered in the statistical analysis section.

Figure 4 shows the same graphs but replaces the mean with the standard deviation of the fraction of killed cops. It is interesting to notice that areas characterized by anarchy, in average terms, are also associated to a high variability of killed cops (see the violet areas). On the other hand, the regions corresponding to the return to the status quo and, even more, the regions of successful revolutions display very low levels of volatility: this means that in
these areas the same outcome is often observed while in the regions in which
anarchy, on average, is observed it is easier to observe another outcome. The
only exception is represented by the graph with \( n = 1.5 \): in fact, in this graph
also the region of successful revolutions is affected by high variability due to the
unique simulation in which no uprising happens.\(^8\)

4 Statistical Analysis

Using the same simulated data employed to draw the four graphs in figure 3 and
4, several statistical models are estimated in order to understand better how the
three outcomes of the model depend on the two precision parameters and the
revolutionaries’ threshold. For the number of killed cops in each simulation it is
assumed a binomial distribution in which the number of attempts is equal to the
number of cops while the probability of success, here the probability of killing a
cop, is a function of the covariates of the model. The covariates include the two
precision parameters, the revolutionaries’ threshold and a set of dummies, one
for each of the ten experiments, to control for the experiments’ heterogeneity.

The model is estimated with different link functions for the probability and
the effect of \( n \) is included in two different ways: with dummies for the values
of the variable in the first specification; with a third degree polynomial in the
second specification.

Results are presented in table 2: in the first column, the linear probability model (LPM) is estimated with ordinary least squares; in the other three
columns, a generalized linear model is estimated with maximum likelihood as-
suming the link function of the logit, probit and cloglog model, respectively.

In all models, the two precision parameters have the expected signs: the preci-
sion of cops has a significant and negative impact on the probability of killing a
cop because the higher the precision of governmental forces, the higher the
number of killed revolutionaries and, consequently, the lower the effectiveness
of revolutionaries in killing cops; on the other hand, the precision of revolution-
aries has a significant and positive effect on the probability of killing a cop and
this is very intuitive.

Finally, more interesting is the effect of the revolutionaries’ threshold. In
the specification with dummies, the baseline is represented by \( n = 0.8 \) and it is
easy to observe that increasing \( n \) up to 1.2 raises the likelihood of killing a cop, \textit{ceteris paribus}. Instead, if \( n = 1.5 \) the probability of killing a cop is
significantly reduced. It is possible to have a graphical representation of this
pattern by substituting the dummies with a third degree polynomial in \( n \). Figure
5 shows these polynomials for the four models; in all of them, it is clear that
the probability of killing a cop is slightly increasing in \( n \) up to a value very close
to 1.2, the maximizer of the function; then, the probability strongly decreases
if \( n \) increases. A third degree polynomial is preferred to a second degree one
because it allows to capture this asymmetry. The intuition behind this shape

\(^8\)The simulation runs are stopped after 300 periods. For \( n = 1.5 \), in one of the ten
simulations no uprising happens within this time.
\[
\begin{array}{cccccc}
& \text{LPM} & \text{LOGIT} & \text{PROBIT} & \text{CLOGLOG} \\
\hline
c & -0.311** & -4.300*** & -2.350*** & -2.241*** \\
& (0.010) & (0.025) & (0.013) & (0.013) \\
r & 1.075*** & 15.404*** & 8.233*** & 7.740*** \\
& (0.017) & (0.060) & (0.031) & (0.031) \\
\text{Dummies for } n: & & & & \\
n = 1 & 0.008 & 0.116*** & 0.063*** & 0.054*** \\
& (0.007) & (0.015) & (0.009) & (0.008) \\
n = 1.2 & 0.011* & 0.153*** & 0.087*** & 0.111*** \\
& (0.007) & (0.015) & (0.009) & (0.008) \\
n = 1.5 & -0.078*** & -0.947*** & -0.599*** & -0.099*** \\
& (0.008) & (0.015) & (0.008) & (0.008) \\
\text{Constant} & 0.678*** & 0.733*** & 0.517*** & 0.165*** \\
& (0.012) & (0.025) & (0.014) & (0.013) \\
\text{Polynomial in } n: & & & & \\
n & -2.137* & -26.005*** & -17.167*** & -22.587*** \\
& (1.187) & (2.836) & (1.594) & (1.493) \\
n^2 & 2.267** & 27.762*** & 18.114*** & 23.142*** \\
& (1.067) & (2.549) & (1.433) & (1.342) \\
n^3 & -0.780** & -9.585*** & -6.198*** & -7.704*** \\
& (0.030) & (0.743) & (0.417) & (0.391) \\
\text{Constant} & 1.336*** & 8.677*** & 5.831*** & 7.268*** \\
& (0.311) & (1.022) & (0.574) & (0.538) \\
\text{Exp. Dummies} & \text{Yes} & \text{Yes} & \text{Yes} & \text{Yes} \\
\text{Observations} & 7480 & 7480 & 7480 & 7480 \\
R^2/pseudo-R^2 & 0.469 & 0.628 & 0.628 & 0.635 \\
\end{array}
\]

Table 2: Estimates of the statistical models. Column 1: linear probability model estimated with ordinary least squares, standard errors corrected for heteroskedasticity. Column 2: logit model estimated with maximum likelihood estimator. Column 3: probit model estimated with maximum likelihood estimator. Column 4: cloglog model estimated with maximum likelihood estimator. (*** significant at 1%, ** significant at 5%, * significant at 10%).
Figure 5: Probability of killing a cop as a function of the revolutionaries’ threshold.
is the following: for a revolutionary organization it is not optimal to start the revolution too early, when popular riots are small-scaled, because it would be easily exposed to the fire of cops but, at the same time, the revolution may not take place if the revolutionary organization waits an excessively big rebellion before coming into action. The optimal behaviour, according to these estimates, is to choose a rule with $n = 1.2$, which means to start the uprising when the number of active agents and revolutionaries exceeds by 20% the governmental forces.

5 Concluding Remarks

The model presented in this paper captures several stylized facts that are common to most real revolutionary phenomena.

First of all, the multiplicity of different scenarios that can arise from a rebellion, i.e., a successful revolution, an anarchic scenario or the return to the status quo. This aspect is particularly significant if we look at the recent experience provided by the Arab Spring, in which many rebellions, started in 2011 in a quite similar way, ended up with completely different political outcomes.

Moreover, this model highlights a plausible dynamic, coherent with the major political revolutions, that can be summarized as follows: a pre-revolutionary period characterized by spontaneous riots motivated mainly by poor economic conditions and social inequality, followed by a proper revolutionary rebellion in which organized and politically oriented elements mobilize the popular masses against the central authority. As we have seen, this dynamic mimics the sequence of events of most historical revolutions and it is consistent with the political science literature that stresses the role played by revolutionary elites in the organization of successful revolutions.

Furthermore, the paper examines the trade-off revolutionaries face in deciding the moment in which coming into action: if they start the uprising too early, when popular riots are small, they are exposed directly to the fire of cops; on the other hand, if they wait an excessively big riot, the revolution may not begin at all. Balancing these two opposite forces, the revolutionary organization finds the optimal threshold and the riots that do not exceed this minimum level of rebels do not degenerate in revolutions.

Finally, this paper stresses the random nature of revolutions pointing out that rebellions arise from the interactions of many agents and this determines their unpredictability: it is not possible to predict with certainty when and which riot will degenerate in revolution. This consideration implies that similar countries, in terms of institutions and political system, may experience revolutionary events at different points in time or some of them may not experience revolutions at all.

A final policy implication concludes the paper. Suppose that a foreign state want to intervene in another one to support a revolutionary group by providing more effective weapons in order to overthrow the existing government. In the framework of the model, this is translated into an increase of the revolutionaries'
effectiveness captured by the parameter $r$. It is also assumed that, without the external intervention, the initial configuration of precision parameters would have led to a rebellion followed by the return to the status quo. If the increase in revolutionaries' precision is not sufficiently large, as shown by the graphs in figure 3, the political situation may degenerate from a relatively stable situation, the return to the status quo (the blue areas in the figure), to a completely unstable one, characterized by a revolution that ends up in anarchy (the lighter blue and white areas in the figure). This is to say that the foreign government should provide enough support in order to deliver a successful revolution as the final result. Mistakes in the calibration of this support may precipitate a country toward a state of civil war.

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