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DIFFUSION OF POPULAR UPRISINGS ACROSS COUNTRIES

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Abstract. A common but unsubstantiated notion is that popular uprising, like those witnessed during the Arab Spring, diffuse across countries. To date, academic research centres on intrastate determinants of political unrest, largely neglecting international considerations. The purpose of this thesis is to examine whether there exists a diffusion of popular uprisings across countries. Synthesizing previous work from the academic fields of revolution and diffusion, we develop a model explaining how transnational spillovers of popular uprisings might occur. The model proposes that an increased level of cultural, political, geographical, and economic closeness of countries facilitates diffusion. To empirically test the existence of such a diffusion pattern, we apply spatial econometric methods to a dataset containing protests and riots directed against government institutions in African states between 1997 and 2012. Our results do not reveal any underlying spatial relations in the data. Thereby, based on our sample and the investigated pattern of diffusion, we find no evidence supporting the notion that popular uprisings diffuse across countries.

Keywords: diffusion, popular uprisings, revolutions, spatial econometrics, Africa

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Contents

‘

Everything is related to everything else, but near things are more related than distant things’

- Tobler’s First Law of Geography, Waldo R. Tobler

Introduction

As 2010 began to draw to an end, the Middle East and North Africa seemed nothing but a politically stable region. In the early days of the new year, however, the situation changed. Tunisia experienced large-scale protests across the country, eventually toppling the regime of President Ben Ali. Within months, other sultanistic regimes in the region had succumbed to similar political unrest: protesters at the Tahrir square ousted the Mubarak-regime in Egypt, al-Qaddafi was captured and killed by Libyan rebels, and President Saleh of Yemen was forced into resigning (Beck, 2014). Following from the initial absence of any organized rebel military force and the relatively short time span of events, the protests accord with Collier and Hoeffler's (2007, p. 714) definition of popular uprisings. In media reports of the events, commonly referred to as the Arab Spring, it was often stated that the popular uprisings spread across the countries in the region. The notion that political unrest diffuses is by no means exclusive to the Arab Spring; for example, the European uprisings of 1848 are frequently described as a revolutionary wave (Baev, 2011; Beissinger, 2007; Weyland, 2009).

Despite these widespread claims of an international connectivity, research on revolution appears predominantly focused on intrastate considerations. Confirming this view, Beck (2014, p. 198) argues that research in the field suffers from 'methodological nationalism', where the international context is systematically neglected. This becomes evident in relation to the diffusion of popular uprisings, as existing work in the academe rarely touches upon the inherently transnational topic (Beck, 2014).

In this thesis, we set out with the purpose of examining whether there exists a diffusion of popular uprisings across countries. Our study addresses two separate fields of academic research: revolutionary activity and diffusion. By synthesizing previous work from the two fields we develop a model for the international diffusion of popular uprisings. The model serves two purposes. First, it presents a mechanism for how popular uprisings may diffuse across countries. Second, building on this mechanism, the model proposes a pattern of diffusion for popular uprisings.

For the empirical analysis, we use country-level data of protests and riots directed at government institutions in Africa during 1997-2012 as a measure of the level of popular uprising. Spatial econometrics, designed to identify and measure spatial interactions, is applied to the data to test whether there exists an international diffusion of popular uprisings. The pattern of diffusion proposed by our model is pivotal in this analysis, as it provides us with necessary guidelines for the econometric specification.

The study is organized in the following fashion. The next section reviews previous research on theories of revolution, economic models of revolution, and diffusion concepts. In the third section we develop a model explaining how popular uprisings diffuse across countries. Section four briefly introduces spatial econometrics, whereafter the econometric specification for our investigation is presented along with testable hypotheses. The fifth section contains our results. In the final section we discuss our main findings in light of the purpose of the study, critically examine potential flaws in our approach, and identify areas for future research.

Previous research

This section presents previous research related to revolution and diffusion. Although the focus of this study lies on popular uprisings, previous literature mainly discusses revolutions. As these two concepts are closely related and, indeed, often used interchangeably, research on revolution carries valuable insights for this study.

Theories of revolution

Dating back to ancient times, some of history's most prominent political theorists have tried to identify the causes of revolution. In his landmark work 'The Republic', Plato argued that the divergent economic interests accompanying poverty give rise to political factionalism and revolutions (Midlarsky & Tanter, 1967). Aristotle (1997, p. 51), being a true disciple of Plato, also stressed that poverty constitutes a precondition for revolutions to occur. In contrast to this view, both Marx and Hegel saw revolutions as outcomes of historical processes (Midlarsky & Tanter, 1967). The former viewed the process as one of class struggle (Engels & Marx, 2008), while the latter, representing German idealism, described it as a conformity process where the social order adjusts to prevailing reasons and ideals (Marcuse, 2000).

More contemporary research attempts to classify the existing theories of revolution. A key contributor is Goldstone (1980), who structures theories on this subject into three broad categories based on their theoretical origin: frustration-aggression theory, structural-functionalist theory, and interest group conflict theory.

The frustration-aggression category–having its roots in cognitive psychology–incorporates theories of revolution that view societal frustration with the political and economic system as the main cause of revolutionary situations. Davies (1962) argues that a period of economic improvement, followed by a sharp reversal, can give rise to such frustration by creating a gap between what people desire and what they can obtain. To support his theory, Davies shows that a J-curve pattern of development, with initial growth and subsequent decline, has preceded several historical revolutions. De Tocqueville highlights that the theories later formalized by Davies in the J-curve, as the theory commonly is known as, can be applied to other considerations than purely economic, such as to changes in the political system (Stone, 1966). However, the J-curve theory is criticized for not recognising the possibility that frustration, being a psychological phenomenon, only is imprecisely related to the material realities (Stone, 1966). Another drawback of the theory is that it provides no criteria regarding the length and size of the growth and decline phases required in order to create a revolutionary setting (Davies, 1962).

While Davies attempts to identify the determinants of frustration, Gurr's (1968) theory of revolution states under what circumstances frustration may lead to revolution. Gurr presents four types of influences. First, government coercion reduces the likelihood of revolutionary outcomes from societal frustration. The second influence, institutionalization, implies that frustration can be managed through institutional mechanisms rather than resulting in revolution. For example, in countries with developed institutional capabilities, people may face high alternative costs associated with the engagement in revolutions, and the presence of political parties and labour unions allow for peaceful ways to express discontent with the status quo. Third, the presence of facilitating factors, such as tools to stage effective revolutions, makes it more likely that societal frustration leads to unrest. The final influence mentioned by Gurr is the legitimacy of the incumbent regime. If the regime is perceived as legitimate, people are more inclined to accept feelings of frustration as a rightful outcome.

The theories of revolution in the structural-functionalist category view societies as networks of subsystems that must be in concordance with each other and their environment in order to be stable (Goldstone, 1980). Any shock that renders the network of subsystems dysfunctional makes society vulnerable to revolution. According to Stone (1966, p. 165), the four most common factors causing dysfunctional systems are 'economic growth, imperial conquest, new metaphysical beliefs, and important technological changes'. A fast and substantial change in any of these four factors is difficult for society to handle, making a revolutionary situation more likely. Research also emphasizes the potential disruptive effects of international competition on domestic stability.

For many years, political aspects such as interstate war dominated academics' thinking when considering international competition (Goldstone, 1980; 2001). Skocpol (1994) broadens the concept by including other considerations, most importantly economic competition. Pressure from international economic forces can severely impair the existing organisation of society, potentially precipitating a revolution.

Drawing on analyses from political science, theories of the interest group conflict category identifies two preconditions that must be fulfilled for revolutions to occur. First, the existing political system must be unable to resolve the interest groups' issues of conflict. Second, more than one of the rival interest groups must have the resources necessary to challenge their opponents using force. These preconditions can arise due to a number of events, including wars, economic development, urbanization, or changing core values. (Goldstone, 1980).

Economic models of revolutions

From an economic standpoint, one of the main issues arising when modelling revolution is the free rider problem of collective action. Tullock (1971) shows, by specifying payoff functions for being inactive or partaking in any of two opposing sides in a revolution, that the public goods aspects (such as the introduction of a more efficient government) will never induce anyone to join the conflict. In reaching this conclusion, Tullock argues that an individual's choice of whether or not to join the ranks of either side in a revolutionary conflict will not affect the probability of a successful revolution. Instead, what motivates an individual to contribute to the efforts of the revolutionaries or the regime is the prospect of reaping private benefits if the revolution succeeds or is supressed, respectively. The private benefits can, for example, be in the form of government office, but also less material gains are possible, such as the entertainment value of participating in mass protests.[1]

Grossman (1991) extends Tullock's reasoning about the role of private benefits into a general equilibrium model of insurrections. The model consists of a kleptocratic ruler who maximizes the expected income of his clientele, and peasant families who maximize their payoff by allocating time between production, soldiering, and insurgency. The ruler controls policy variables such as the level of taxes and rent extraction, and the number of soldiers employed by the regime. Furthermore it is assumed that the benefits of a successful revolution are excludable, that is, the

[1] Tullock includes the entertainment value of participating in mass protests in his payoff function for protesters, but at the same time argues that it in most cases has a quite small impact. As exceptions he mentions 'pseudorevolutions' where there is little to be gained and only a minor risk of being hurt from participating–such as in the student revolutions of the late 1960's.

benefits are private to those who participate in the insurgency. The main contribution by Grossman's model is the introduction of exogenous technologies of insurrection and suppression that determine the effectiveness of insurgents and soldiers, respectively. By using these technologies to adjust for effectiveness, the number of insurgents relative to the number of soldiers determines the probability of a successful revolution. By way of simulation, Grossman shows that the technologies of insurrection and suppression govern how the ruler makes policy choices and how the peasant families allocate their time.

There exist several additional models of revolution that build on the concept of private benefits. In one of the more prominent contributions, Kuran (1989) sets out to explain why many revolutions are unanticipated. The novelty introduced in his model is the incorporation of agents that have public as well as private political preferences. The agents derive utility from their public preference, as in Tullock (1971) and Grossman (1991), but they also derive disutility from any potential dissonance between their public and private preferences. Kuran calls this dissonance preference falsification–it compromises an agent's integrity. For example, despite privately supporting the opposition, an agent may publicly portray himself as loyal to the regime in order to maximize his utility. In situations where many agents engage in preference falsification of this kind, Kuran shows that only a minor event is needed to trigger a revolutionary bandwagon capable of overthrowing the regime. This explains why apparently stable societies may suddenly face political uprisings.

Although the introduction of excludable benefits is the most widespread solution to the free rider problem in models of revolution, it is not uncontested. An alternative solution is put forth by Roemer (1985). An imaginary revolutionary leader–called Lenin–only promises social non-excludable benefits if there is a regime change, and overcomes the associated free rider problem by using his charisma (Roemer, 1985). However, Tullock (1974, p. 45) criticizes this view by noting that the real Lenin in fact promoted the use of 'professional revolutionaries' who were promised excludable benefits should the revolution succeed.[2] Along this line of thought, Grossman (1995; 1999) extends his general equilibrium model of insurrections from 1991 to include a revolutionary leader whose function is to recruit, compensate, and deploy insurgents. Also Kuran (1989) argues that revolutionary leaders act to enhance the benefits of joining the revolution, and further adds that they shape and uncover the population's private political preferences.

[2] It should be noted that social non-excludable benefits do not preclude excludable private benefits. Therefore, models emphasising social benefits should be viewed as complementary rather than competing to those emphasising private benefits (Grossman, 1995).

It is noteworthy that none of the presented economic models of revolution formally incorporate an international setting. When potential international effects are mentioned, they are treated as exogenous stimuli in the form of foreign support for the regime or opposition (Kuran, 1989; Grossman, 1999). Also missing is a formal inclusion of time. The models, in their current states, are thus not appropriate to explain a potential diffusion of popular uprisings across countries, as both an international setting and time are needed in this process.

Technology diffusion

Research on diffusion of technological innovations spans across many social sciences, including geography, sociology, marketing, and economics (Mahajan & Peterson, 1985; Young, 2009). Despite differences in nature between some of these academic domains, they all have one main finding in common when it comes to diffusion research: the cumulative adoption time path of innovations follows an S-shaped curve (Mahajan & Peterson, 1985). Expressed in words, the S-shaped curve implies that an increasing number of individuals adopt an innovation in the initial time periods. At some point in time this trend reverses, and the number of adopters in each time period starts to fall. Eventually, the total number of adopters reaches an asymptotic limit. Although this is the general pattern of technology diffusion, the slope and point of inflection may vary between different S-shaped diffusion curves (Mahajan & Peterson, 1985).

In general terms, diffusion research seeks to explain why technology diffusion follows an S-shaped curve. The literature on this topic is vast, and there seems to be no approach or classification within diffusion research that is more accepted than any other. In this subsection, we choose to follow the classification of Young (2009), who defines three broad classes of diffusion theories and models: contagion, social influence, and social learning.

In contagion models of innovation diffusion, people in a social system adopt an innovation by being exposed to it.[3] There are two sources of contagion: one from within the social system, and one from outside the social system. The within influence is transmitted through social interaction between prior adopters and potential adopters. Contagion emanating from outside the social system is often defined as all the influence not stemming from prior adopters within the social system. This influence can, for example, be transmitted through mass media communication or change agents (Mahajan & Peterson, 1985).

[3] The contagion type of model can be found under other names: mixed-influence model (Mahajan & Peterson, 1985), Bass model (Young, 2009), and epidemic model (Geroski, 2000).

A central concept in contagion models of diffusion is homophily. It implies that people are more prone to adopt an innovation if they are more alike the source influencing them. Besides the fact that the source has knowledge about the innovation, for the diffusion to occur as rapidly as possible, the source and adopter should be identical in all aspects (Rogers, 2003).

Social influence models emphasize a conformity motive in the diffusion of innovations. People adopt innovations due to a perceived pressure to follow trends in the social system. In standard social influence models it is often assumed that an agent's choice of whether to adopt depends on the number or proportion of existing adopters. Each agent has his own threshold value of existing adopters at which he succumbs to the social pressure and adopts the innovation (Young, 2009).

In contrast to social influence models, where the current popularity of an innovation drives the diffusion process, social learning models focus on the track record of innovations. By observing outcomes among prior adopters of an innovation, the agents in social learning models form opinions regarding whether or not adopting the innovation is beneficial. While the two previous approaches to innovation diffusion only state that people will adopt when others adopt, the social learning category of diffusion models provides an answer to why this is the case: utility maximizing agents make rational decisions based on the cumulative experience of prior adopters. (Young, 2009).

A model for the diffusion of popular uprisings

In this section we develop a model for the international diffusion of popular uprisings. The process is divided into four parts. First, we present a framework for uprisings based on Kuran's (1989) model. We advance this framework by introducing technologies for the regime and opposition. In the second part of this section, we show how these technologies diffuse across countries by using Young's (2009) exposition of the contagion model. Based on theories from political science and business science, we argue that the rate of technological diffusion depends on how close countries are. To complete the model, we integrate the international diffusion of technology into the framework for uprisings in the third part of the section. Finally, we present the proposition following from the model: it becomes easier for uprisings to diffuse across countries if they are close.

In the model, we refer to the political party in power as the 'regime'. The Concise Oxford English Dictionary (2011) defines regime as 'a government, especially an authoritarian one'. Still, the model we develop is also applicable to democratic states. As a democratically elected government may deviate from its election promises, a situation as described by the model can arise where the people turn against their elected politicians. However, this risk is likely to be mitigated by the presence of political institutions.

Specification of a framework for popular uprisings

Following the approach of Kuran (1989), let us consider a country where the political scene is unidimensional: all possible social orders p are on the interval $[0,1]$. In reality, there probably exists more than one dimension, but people tend to simplify differences onto a single scale. A case in point is the left-right political spectrum. Furthermore, the country has two opposing political parties. The incumbent regime represents social order $p = 0$. The opposition challenges the regime's authority and advocates social order $p = 1$. Each party consists of activists who are fully committed to the party's preferred social order.

There are N citizens in the country, all of whom are assumed to be non-activists. They are associated with neither of the two political parties; instead each individual i alters his public political preference $y^i = [0,1]$ to maximize his expected benefits. The distribution of power between the two parties is determined by the collective sentiment in the country, given by a weighted average of the citizens' public preferences

$$\hat{y} = \sum_{1}^{N} w^i y^i \tag{1}$$

The weights w^i sum to unity and represent individual i's influence in society. For example, a prominent religious leader may have greater influence on the collective sentiment than a peasant.[4] The notion that the distribution of political power–and thus the determination of social order–stems from the collective sentiment in a country dates back to Hume (Kuran, 1989). In the current framework, a collective sentiment of $\hat{y} = 0$ implies that the regime can run the country as it wishes. A popular uprising takes place when the collective sentiment substantially and rapidly shifts in favour of the opposition.

In addition to the public preference, each citizen i has a private political preference $x^i = [0,1]$. The private preference is determined exogenously and expresses how a citizen would vote in a

[4] It should be noted, however, that even the most influential citizen probably only has a marginal impact on the collective sentiment in a country.

secret ballot. In contrast, the public preference that a citizen chooses to declare is affected by two considerations. First, the citizens incur reputational utility from being known as having a particular political stance. Second, any potential dissonance between a citizen's private and public preferences–called preference falsification– leads to disutility by compromising the citizen's integrity. Expressed in a more formal way, citizen i's utility from declaring public preference y^i is

$$V^i(y^i|x^i) = Q(y^i) + N(y^i|x^i) \tag{2}$$

where $Q(y^i)$ is the reputational utility and $N(y^i|x^i)$ is the utility from integrity.[5]

In order to specify the reputational utility $Q(y^i)$, some additional concepts must first be defined. Let R be the sum of the weighted influence of the citizens supporting the regime, and O be the sum of the weighted influence of the citizens supporting the opposition. Furthermore, let $\beta(t) > 0$ be the time-variant technology used by the regime to stay in power, and $\alpha(t) > 0$ be the opposition's time-variant technology used to challenge the regime. The regime's and opposition's technologies are novelties introduced by us in the model, and we will later specify how they are determined. For now, however, it suffices to know about their existence.[6] The reputational utility from being known as y^i is given by

$$Q(y^i) = \begin{cases} f(R, \theta(t))\ if\ y^i = 0 \\ 0\ if\ 0 < y^i < 1 \\ F(O, \theta(t))\ if\ y^i = 1 \end{cases} \tag{3}$$

where $\theta(t) = \frac{\alpha(t)}{\beta(t)}$ is the relative level of technology, and the following properties apply

$$f(0, \theta(t)) > 0 \qquad \lim_{\theta(t)\to\infty} f(R, \theta(t)) = 0 \qquad \frac{\partial f}{\partial R} > 0 \qquad \frac{\partial f}{\partial \theta} < 0$$

$$F(0, \theta(t)) > 0 \qquad \lim_{\theta(t)\to 0} F(O, \theta(t)) = 0 \qquad \frac{\partial F}{\partial O} > 0 \qquad \frac{\partial F}{\partial \theta} > 0$$

The first two properties of each function give that reputational utility never can be lower than zero. The reputational utility of both regime and opposition supporters increases with the weighted influence of the supporters of each party, as given by the third property. Furthermore,

[5] Non-excludable benefits related to the social order are not included in the utility function. Due to the small impact each citizen has on the collective sentiment, the citizens treat the utility derived from the social order as fixed.

[6] Compared to Kuran's original model, one main limitation arises from introducing regime and opposition technologies. This limitation–which is related to the framework's applicability in the event of regime change–is further discussed near the end of this section.

in the last property, an increase in the relative strength of the opposition technology raises the reputational utility of opposition supporters, while an increase in the relative strength of the regime technology raises the reputational utility of regime supporters.

Some of the above properties deserve to be justified. The outcome that citizens get no reputational utility from not fully supporting the regime or opposition is a simplification, but is consistent with the observation that established political parties maltreat and discredit mavericks in order to avoid political balkanization (Kuran, 1989). Furthermore, the utility derived from supporting any of the two political factions is increasing with the size of the party. This implies a type of 'economies of scale' in reputational utility, which is generated by supporters providing each other with implicit benefits, for example a sense of belongingness (Kuran, 1989). Finally, an increase in the relative strength of the opposition's technology enhances their ability to provide benefits to its supporters, while those loyal to the regime become worse off. The rationale behind focusing on the relative strength is the fact that most, if not all, future benefits from supporting the regime or the opposition are scaled by a probabilistic factor that the party one supports will be in power in the future. Consistent with Grossman (1991; 1995; 1999), this probabilistic factor depends on the relative level of technology of the two parties.

Turning to the utility derived from integrity in (2), it is defined as

$$N\left(y^i \middle| x^i\right) = N\left(1 - \left|x^i - y^i\right|\right) \tag{4}$$

The domain of $N\left(y^i \middle| x^i\right)$ is $[0,1]$ and $\max N\left(1 - \left|x^i - y^i\right|\right) = N(1)$. Thus, the utility from integrity is maximized when the public preference equals the private preference, $y^i = x^i$.

By inserting (3) and (4) into (2), three distinct cases of citizen i's utility-maximizing choice of public preference y^i are rendered:

$$\begin{cases} V^i\left(y^i = 0 \middle| x^i\right) = f\left(R^e, \theta(t)\right) + N\left(1 - x^i\right) \\ V^i\left(y^i = x^i \middle| x^i \notin \{0,1\}\right) = N(1) \\ V^i\left(y^i = 1 \middle| x^i\right) = F\left(O^e, \theta(t)\right) + N\left(x^i\right) \end{cases} \tag{5}$$

R^e and O^e are the expected shares of support for the regime and opposition, respectively. However, for reasons of tractability, it is hereafter assumed that for all citizens the utility from supporting either the regime or the opposition strictly dominates the utility from not supporting any of the two parties. It is thus beneficial for every citizen with $x^i = (0,1)$ to engage in preference falsification and set y^i equal to zero or one.[7] The maximization problem facing citizen i therefore reduces to

$$\begin{cases} V^i(y^i = 0|x^i) = f(1 - O^e, \theta(t)) + N(1 - x^i) \\ V^i(y^i = 1|x^i) = F(O^e, \theta(t)) + N(x^i) \end{cases} \tag{6}$$

where $O^e + R^e = 1$ because every citizen sides with either the regime or the opposition. Holding $\theta(t)$ fixed, it can be shown that a higher value of O^e reduces the private preference x^i where citizen i is indifferent between choosing $y^i = 0$ and $y^i = 1$.[8]

Figure 1 depicts this relationship at time t, where a citizens with $[O^e, x^i]$ above the threshold function $\underline{x}_t^i(O^e)$ chooses to side with the opposition, while publicly supporting the regime otherwise.[9]

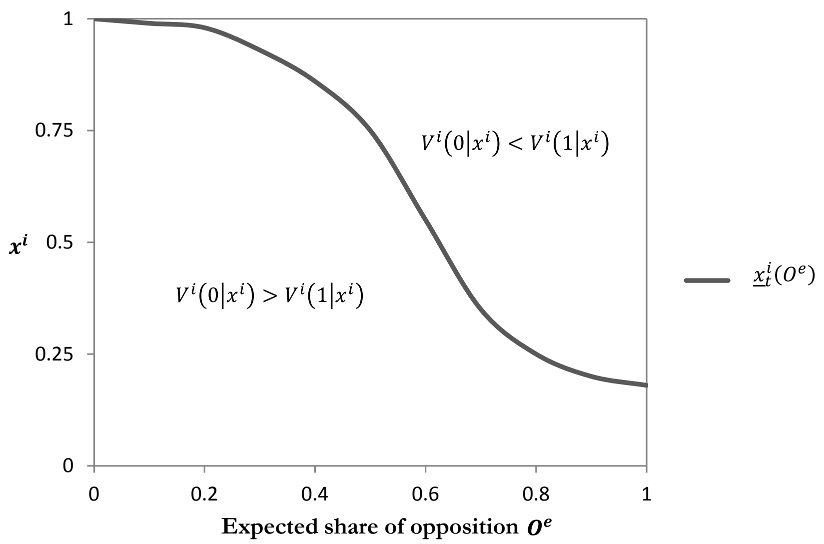


Figure 1: Threshold function $\underline{x}_t^i(O^e)$.

With the intention to focus on private preferences and, later, technology diffusion, it is assumed that all citizens i have the same expectation of the opposition's share of support O^e as well as identical utility functions. The threshold function thereby becomes identical for all citizens and consequently provides a range of private preferences for each O^e where it is optimal to side with the opposition. Figure 2 introduces the cumulative weighted density of private preferences, $g(x)$,

[7] It is noteworthy that this assumption does not compromise the role of integrity, as the citizens still can choose not to support the party offering them the greatest reputational benefits.
[8] For derivations, see Appendix A.
[9] In line with (Kuran, 1989), the threshold function in Figure 1 is arbitrarily drawn.

which provides the weighted influence of citizens with private preferences $x^i > x$ along the top horizontal axis.

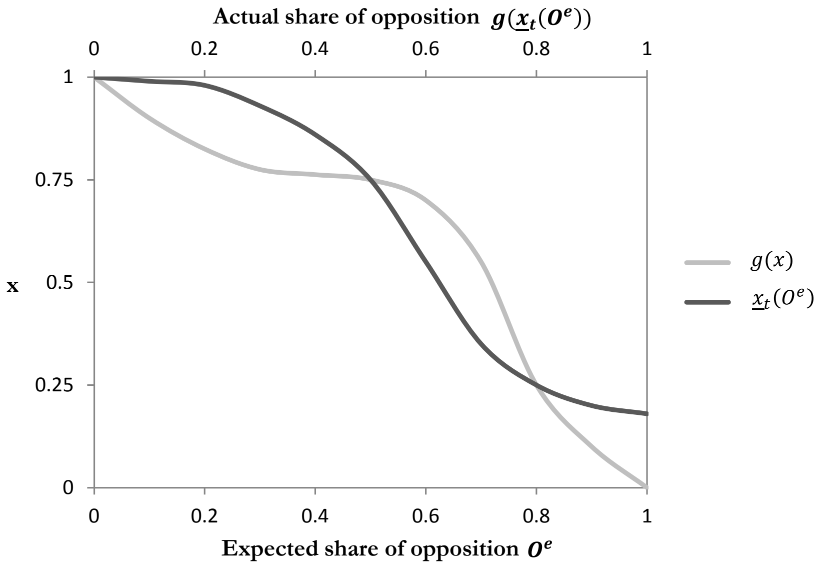


Figure 2: Threshold function $\underline{x}_t(O^e)$ and cumulative weighted density function $g(x)$.

For each expected size of the opposition O^e, the actual weighted opposition support at time t is given by

$$O = g(\underline{x}_t(O^e)\,) \tag{7}$$

The system is in disequilibrium as long as $O \neq O^e$, causing the citizens to revise their expectations until equilibrium is found at $O = O^e$.[10] However, not all equilibria are stable. In Figure 2, the equilibria at 0 and 0.8 are stable, as any minor deviation of the expected share of opposition from these equilibria will be forced back. In contrast, any deviation from the equilibrium at 0.5 will precipitate a bandwagon effect that will halt first upon reaching one of the stable equilibria. Therefore, the equilibria at 0.5 is said to be unstable. In brief, a popular uprising occurs when the equilibrium for the political order shifts substantially. This can take place due to revised expectations of the opposition's share of support O^e, or through a shift in the threshold function $\underline{x}_t^i(O^e)$.

[10] In equilibrium, the social order in the country is not necessarily at a standstill. Rather, it implies that the *direction* of change in the social order, determined by the collective sentiment, is stable.

International diffusion of technology

We now turn our attention to the technologies $\beta(t)$ and $\alpha(t)$ that we introduced into the framework for popular uprisings. In line with our prior reasoning, each party has its own distinct technology. The regime applies its technology to prevail, whereas the opposition technology is used to challenge the regime. Technology is a broad concept and includes both material as well as immaterial innovations (Mahajan & Peterson, 1985). In the case of popular uprisings, an example of material technological innovations could be the regime's use of internet surveillance, while the opposition's use of ideology or religion to provide benefits to its supporters could act as an example of immaterial innovations. Ultimately, the parties' technologies affect the reputational utility incurred by their supporters.

We postulate that the technologies are set by the activists in the parties, as they decide on how their respective organizations operate. The level of adoption of a new technological innovation is assumed to be reflected by the proportion of activists who have adopted it. That is, a new technology is fully implemented when it has been adopted by all activists in a party.[11]

Technological innovations are developed internally by the activists of the regime or opposition in our country of interest, but may as well originate from regimes or opposition parties in other countries. In order to be able to focus on the consequences of the international diffusion of technology, we abstract from internal sources of technological development in the following discussion.[12] We propose that the diffusion of regime and opposition technologies across countries mainly occurs during uprisings. This owes to two factors. First, new technologies are developed and tested during popular uprisings. This experience base serves to reduce the risk for later adopters, which facilitates the diffusion (Young, 2009). Second, the attention created around popular uprisings enhances the technology diffusion through, for example, media coverage of the events (Mahajan & Peterson, 1985; Rogers, 2003).

To formally express how the regime's and opposition's technologies are affected by international technology diffusion, let us assume that a popular uprising takes place in another country at time t_0. Drawing on the experiences from this uprising, new technologies diffuse to our country

[11] One could argue for alternative ways to measure the level of adoption of a new technology. A possibility is a binary approach where the technology is fully implemented as soon as the party leader has accepted it. However, we believe that our assumption is the most suitable in an organizational setting, as many new technologies cannot be fully implemented unless all organizational members understand and accept them.

[12] In our framework, this abstraction is equivalent to assuming an equal rate of change in the regime's and opposition's technologies owing to internal factors.

of interest, which, when fully adopted, improve the regime's and opposition's respective technologies by a fraction δ. This can be expressed as

$$\alpha(t) = \alpha_{t_0}\big(1 + \delta * P_O(t)\big) \tag{8}$$

$$\beta(t) = \beta_{t_0}\big(1 + \delta * P_R(t)\big) \tag{9}$$

where $P_O(t)$ and $P_R(t)$ are the proportions of opposition activists and regime activists who have adopted the new technologies at time t, respectively. It may appear controversial that we use the same change fraction δ for both parties, without taking into account the characteristics or the outcome of the uprising from which the diffusion originates. However, we motivate this by our observation that the development of two conflicting technologies, as in this case, tends to be closely interrelated. An example could be the common notion that technological improvements by criminals put pressure on the police to improve its technology. Therefore, we believe that an equal change fraction for the technologies used by the regime and opposition is a plausible case. Furthermore, on an intuitive level, if either the regime or opposition technology systematically improves at a faster rate than the other, we would in the long run only observe stable regimes or constantly reoccurring popular uprisings. To our awareness, no such trend exists.

Based on Young's (2009) description of the contagion model of technology diffusion, the proportion of opposition and regime activists who have adopted the new technologies at time t is affected by two rates of contagion. First, external contagion is present at a rate of γ per time unit from the country originating the diffusion. Second, when the new technologies gain a foothold in our country of interest, internal contagion arises as the technologies spread among activists at a rate of ω per time unit. The total rate of adoption among regime and opposition activists can thus be expressed as

$$\dot{P}_O(t) = (\omega_O P_O(t) + \gamma_O)\big(1 - P_O(t)\big) \tag{10}$$

$$\dot{P}_R(t) = (\omega_R P_R(t) + \gamma_R)\big(1 - P_R(t)\big) \tag{11}$$

The solutions to these first-order non-linear differential equations under the initial conditions $P_O(0) = 0$ and $P_R(0) = 0$ are given by:[13]

[13] For derivations, see Appendix B.

$$P_O(t) = \frac{\left(1 - e^{-(\omega_O + \gamma_O)t}\right)}{\left(1 + \left(\frac{\omega_O}{\gamma_O}\right) e^{-(\omega_O + \gamma_O)t}\right)} \tag{12}$$

$$P_R(t) = \frac{\left(1 - e^{-(\omega_R + \gamma_R)t}\right)}{\left(1 + \left(\frac{\omega_R}{\gamma_R}\right) e^{-(\omega_R + \gamma_R)t}\right)} \tag{13}$$

$P_R(t)$ and $P_O(t)$ give the proportions of regime activists and opposition activists who have adopted the diffusing technologies at time t. The cumulative adoption of the diffusing technologies follows an S-shaped curve over time, which is consistent with most observed diffusion patterns (Mahajan & Peterson, 1985).

Expressions (12) and (13) provide the framework for a contagion-based diffusion model. Adding to this framework, we postulate that the internal rates of contagion of the two parties are equal, $\omega_O = \omega_R$, and that the rates of external contagion from the country emanating the new technologies, given by γ_R and γ_O, depend on the cultural, political, geographical, and economic closeness of the two countries.[14] These four factors are the main attributes of the CAGE distance framework developed by Ghemawat (2011) to assess the ease of international expansion for businesses.[15] In essence, the CAGE framework states that international expansion is facilitated by increased cultural, political, geographical, and economic proximity between countries. In our model, these four factors are captured by the term $c = [0,1]$, where a value close to zero indicates that the countries are 'far apart', while a value close to one means that the countries are 'close'. Formally, the above can be expressed as $\gamma_R = \gamma_R(c)$ and $\gamma_O = \gamma_O(c)$. We assign them the following properties

$$\frac{\partial \gamma_R(c)}{\partial c} > 0, \frac{\partial \gamma_O(c)}{\partial c} > 0$$
$$\gamma_O(0) - \gamma_R(0) = 0, \frac{\partial(\gamma_O(c) - \gamma_R(c))}{\partial c} > 0$$

The first two properties, that γ_R and γ_O are increasing in c, are in accordance with the reasoning of the CAGE framework and imply a higher rate of external contagion the closer two countries

[14] The property $\omega_O = \omega_R$ is motivated by noting that the activists of the two parties, apart from their divergent political opinions, share many country-specific features, such as common culture, norms, history, and social structures. These similarities contribute to the creation of comparable patterns of social interaction within the two parties. As social interaction is the determinant of the rate of internal contagion, we arrive at the property $\omega_O = \omega_R$ (Mahajan & Peterson, 1985).

[15] CAGE is an acronym for Culture, Administrative, Geography and Economic. In our text, we opt for 'political' instead of 'administrative', as it falls closer to the focus of this study.

are. More important for our analysis are the last two properties. Combined, they imply that when two countries are far apart (as measured by c), the rate of external contagion of regime technology and the rate of external contagion of opposition technology are close to equivalent, but as the two countries get closer, the rate of external contagion of opposition technology becomes greater relative to that of the regime technology. We motivate this property based on the concept of mutual empowerment, originally coined by Spruyt (1994). Mutual empowerment is the tendency of political actors to strengthen themselves by creating similar actors and situations elsewhere. In the context of international diffusion of popular uprisings, activists undertaking an uprising in one country are incentivized to instigate similar revolutionary situations in other, currently stable, countries. Likewise, opposition activists in the stable countries face the same incentives from mutual empowerment, and are thus more likely to rebel when uprisings similar to their own cause are unfolding in other countries. In accordance with this line of thought, Beissinger's (2007) exposition of popular uprisings in authoritarian post-communist states in the early 21th century reveals how opposition groups formally supported each other, across country borders, with effective revolutionary practices and know-how. Based on this observation, attempts to diffuse uprisings to stable countries seem to mainly occur through a transfer of opposition technology. Furthermore, the concept of mutual empowerment stresses the creation of *similar* actors and situations, which presumably becomes easier if two countries already have similar cultural, political, economic, and geographical characteristics. The incentives provided by mutual empowerment are thus strengthened as c increases. In contrast, a regime subject to uprisings will initially–irrespective of c–not face any strong incentives from mutual empowerment to transfer their technologies to stable countries, as political stability is the setting preferred by the regime.

In brief, the above reasoning implies that when countries are far apart, the concept of mutual empowerment does not incentivize opposition activists to share their technologies, as it is too difficult to create a similar actor or political setting in the other country. This justifies the property $\gamma_O(0) - \gamma_R(0) = 0$, under the assumption that there is no other systematic difference in the regime's or opposition's ability to transfer or receive new technologies apart from the effects of mutual empowerment. However, when two countries are close, it becomes easier to instigate a similar political uprising in the other country, and opposition activists in both countries become more prone to exchange their opposition technologies due to the incentives provided by mutual empowerment. The rate of contagion of opposition technology from external sources thus grows faster in c than the rate of contagion of regime technology from external sources, as expressed by $\frac{\partial(\gamma_O(c)-\gamma_R(c))}{\partial c} > 0$.

By introducing (12) and (13) into the expressions determining the regime's technology (8) and the opposition's technology (9), we can examine how the levels of technology for the two parties' depend on c during a diffusion process across countries. This is illustrated in Figure 3 and Figure 4, where the technological innovations from a popular uprising in a country at time $t_0 = 0$ diffuse to the regime and opposition activists in our country of interest.

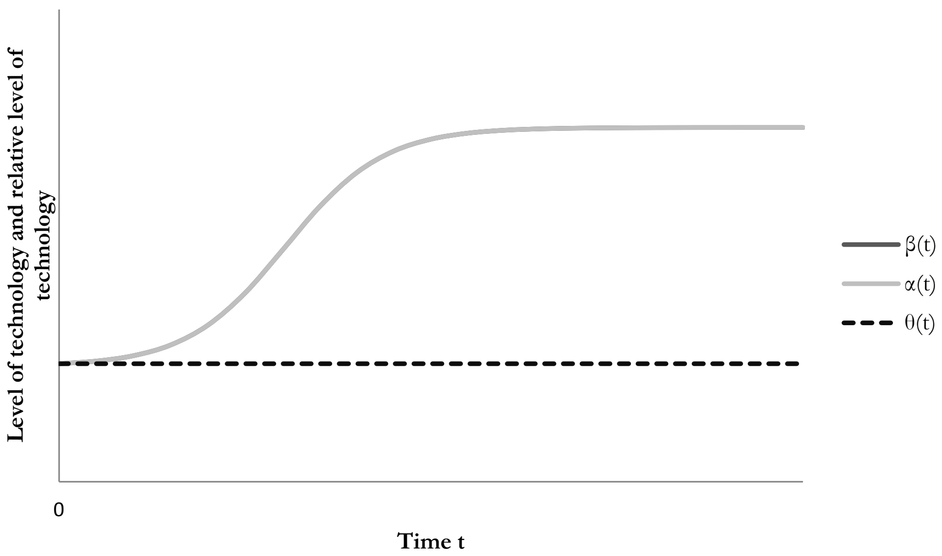


Figure 3: When countries are distant, the rates of technology diffusion for the regime and opposition coincide. The relative level of technology remains constant during the diffusion process.

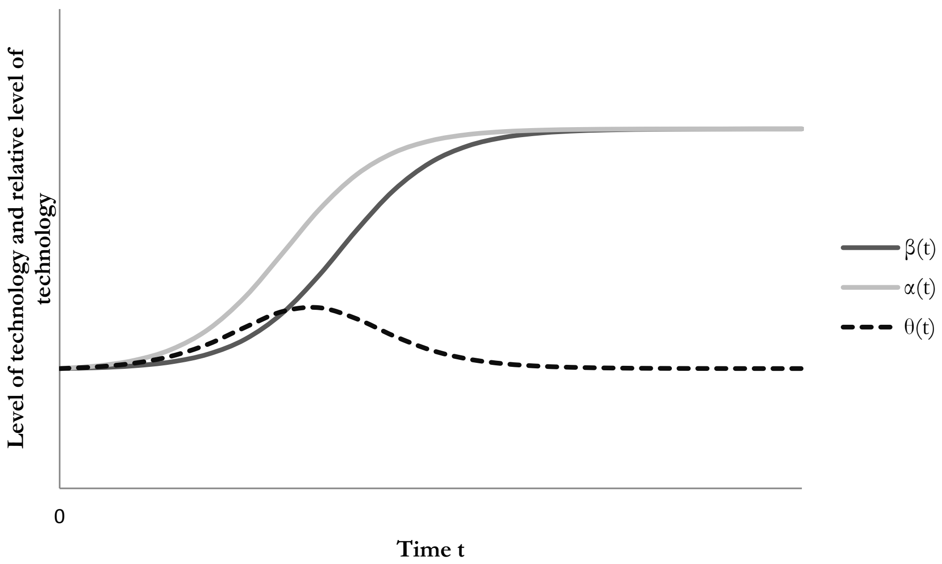


Figure 4: When countries are close, the opposition experiences a faster rate of diffusion than the regime. The relative level of technology temporarily increases during the diffusion process.

In Figure 3, the two countries in a diffusion process are distant, given by a value of c close to zero. As illustrated, in this case the diffusion of the regime technology coincides with the diffusion of the opposition technology. The relative level of the two parties' technologies $\theta(t)$ thus remains constant over time. However, if two countries are close, as measured by a value of c approaching a value of one, the diffusion of regime technology and opposition technology no longer occurs at the same rate due to different values of γ_R and γ_O. This situation is depicted in Figure 4. The relative level of the two parties' technologies is no longer constant; instead it experiences a spike during the diffusion process, after which it returns to the pre-diffusion level. Let t_{max} be the time at which the spike peaks during the diffusion process, or, expressed more formally, the local solution to $\max_t \theta(t)$.[16]

Technological diffusion in the framework for popular uprisings

We are now ready to examine the effects of international technology diffusion on our framework for popular uprisings. Recall that we introduced the relative level of technology $\theta(t)$ into the citizens' utility maximization problem:

$$\begin{cases} V^i(y^i = 0|x^i) = f(1 - O^e, \theta(t)) + N(1 - x^i) \\ V^i(y^i = 1|x^i) = F(O^e, \theta(t)) + N(x^i) \end{cases}$$

As previously defined, let $\underline{x}_t(O^e)$ be the threshold function at time t. For any given O^e, it can be shown that a higher value of $\theta(t)$ reduces the private preference x^i where citizen i is indifferent between choosing $y^i = 0$ and $y^i = 1$.[17] Thus, if the relative technology level is constant during the diffusion process, as is the case when countries are far apart, $\underline{x}_t(O^e)$ will not shift over time. This situation is depicted in Figure 5, where $\underline{x}_t(O^e) = \underline{x}(O^e)$.

[16] For illustrative purposes, we have set $\alpha_{t_0} = \beta_{t_0}$ in Figure 3 and Figure 4. It should be noted that the results derived in this section are not sensitive to the values of α_{t_0} and β_{t_0}.

[17] For derivations, see Appendix C.

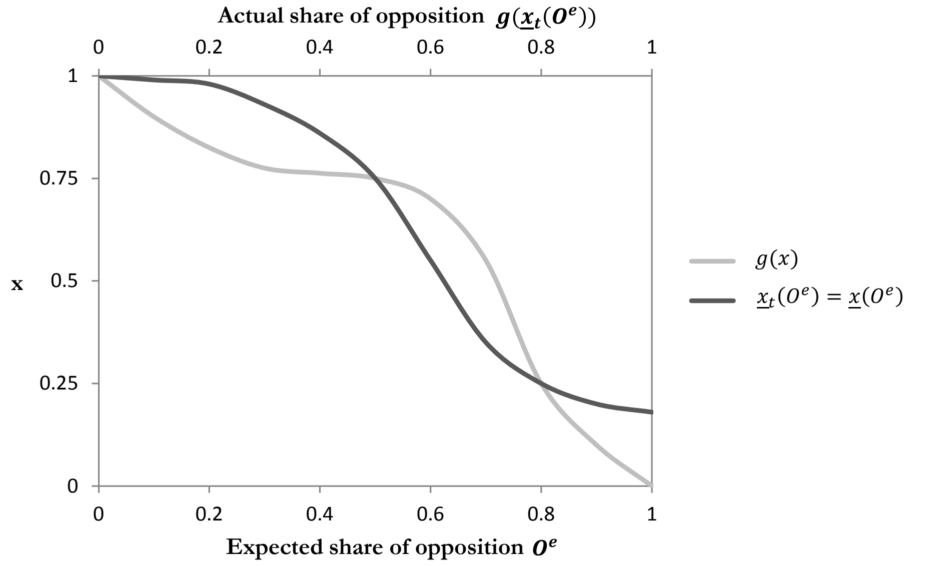


Figure 5: When countries are distant, no shift in the threshold function takes place during the diffusion process.

However, when two countries are close, opposition technology diffuses at a faster rate than regime technology, giving rise to a temporary increase in $\theta(t)$. The initial threshold function before the start of the diffusion of new technologies, $\underline{x}_{t_0}(O^e)$, shifts down over time until it reaches $\underline{x}_{t_{max}}(O^e)$. After time t_{max}, the relative level of technology $\theta(t)$ gradually returns to its pre-diffusion level, causing the threshold function to shift up to its original position in the long run.

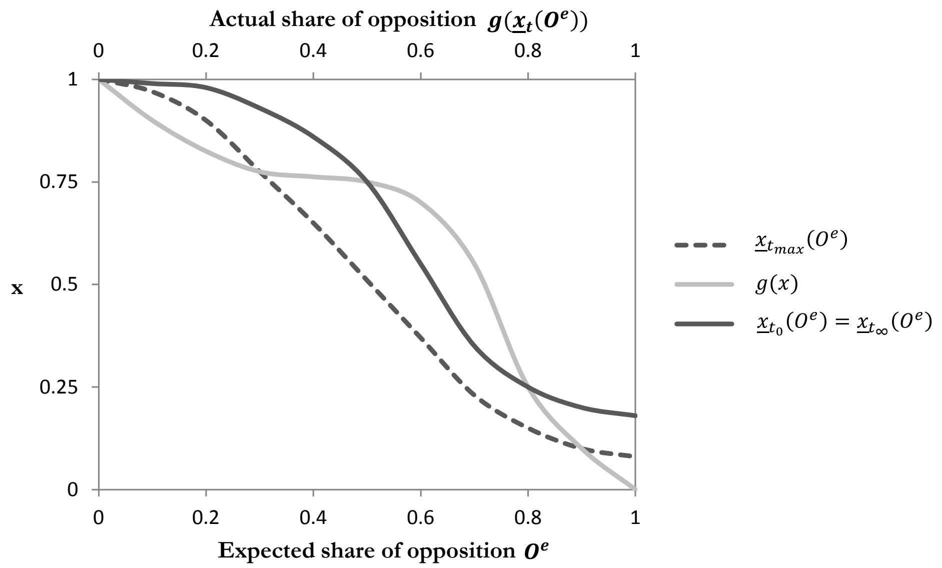


Figure 6: When countries are close, the threshold function shifts down during the diffusion process.

Given that the country at time t_0 is in a stable equilibrium at 0, the downward shift of the threshold function in Figure 6 lowers the required increase in the citizens' expected share of opposition for a popular uprising to start. At time t_0 an expected share of opposition greater than 0.5 is required to instigate a revolution. This level is gradually lowered to 0.3 at time t_{max}, and returns to 0.5 at time t_∞. The time between t_0 and t_∞ thus constitutes a 'window of opportunity' during which it becomes easier for a popular uprising to start.

Furthermore, if the downward shift of the threshold function is substantial, it can precipitate a popular uprising by itself. This situation is illustrated in Figure 7, where 0 no longer is equilibrium at time t_{max}. Instead, a new and sole equilibrium is established at 0.9. A popular uprising takes place as the collective sentiment in the country shifts in the direction of the opposition. Also in this case the start of a popular uprising is facilitated during a 'window of opportunity'.

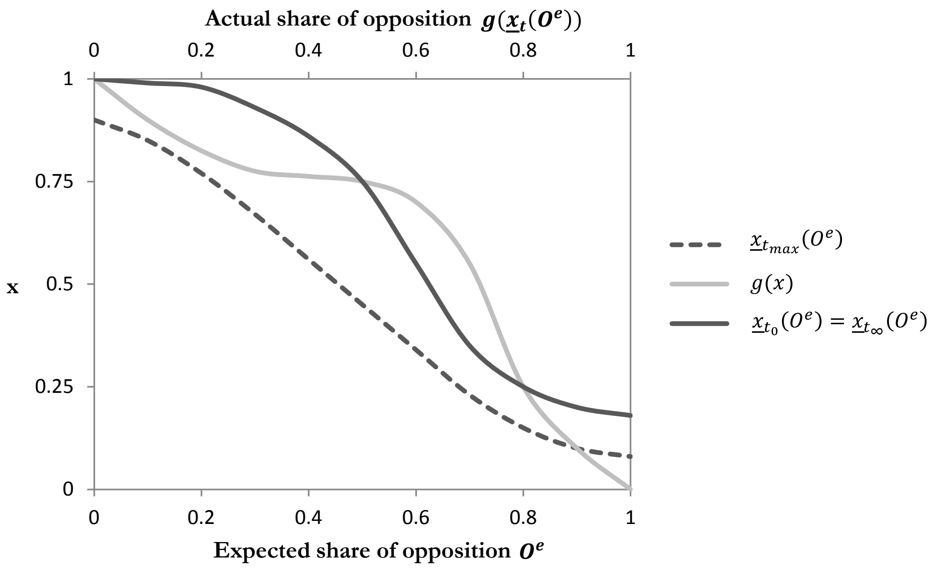


Figure 7: If the shift in the threshold function is substantial, the original equilibrium at 0 is rendered obsolete.

A popular uprising is either unsuccessful or successful in ousting the incumbent regime. If it is unsuccessful, the threshold function eventually shifts back to its original position. The country thus returns to the pre-diffusion set E of possible equilibria for the social order. For example, in Figure 7, $E \in \{0, 0.5, 0.8\}$. However, we cannot specify which equilibrium the country returns to.

After a successful popular uprising where the opposition replaces the regime, the current framework can no longer explain the internal political developments in the country. The original regime has to reorganize from a regime technology to an opposition technology, whereas the original opposition has to reorganize in the opposite direction. This outcome is caused by our introduction of technologies, and deviates from Kuran's (1989) model. It is probably possible to extend our framework to account for the consequences of regime change. However, as we focus on the international diffusion of popular uprisings, and not on their eventual outcomes, this falls beyond the scope of this study.

Predictions of the model

We focus on the predictions of the model that are related to the international diffusion of popular uprisings. Most other predictions of the model are consistent with Kuran's (1989) original work.[18]

> *Proposition 1*
>
> *The closer two countries are, as measured by c, the easier it becomes for a popular uprising in one of the countries to diffuse to the other.*

As mentioned before, the parameter c measures the closeness of countries on four main scales: cultural, political, geographical, and economic. In the next section, covering the empirical method, we will formulate testable hypotheses based on the pattern of diffusion for popular uprisings suggested by Proposition 1.

Empirical method

To empirically test for the presence of diffusion of popular uprisings across countries, we apply certain econometric methods. These methods, able to model and control for spatial diffusion, are found in the field of spatial econometrics. As will be apparent, however, empirical specification of spatial models involves a certain degree of arbitrariness and few, if any, theoretical or practical guidelines when modelling for diffusion of popular uprisings. Therefore, Proposition 1 is crucial to our empirical study, as it provides us with necessary guidelines when specifying this diffusion pattern.

The following subsection elaborates on why we are required to rely on a limited scope of estimation methods. It thereafter presents the econometric specification of the two estimation methods we use, as well as the intuition behind them. In the second subsection, we discuss how

[18] As previously discussed, the outcome deviating from Kuran's (1989) original model, although somewhat limiting in itself, occurs after the event of a popular uprising, and is thus not a cause of concern given the purpose of this study.

to model for spatial diffusion patterns. The third subsection continues with data and variables specification. Finally, we formulate hypotheses based on Proposition 1.

Spatial econometric specification

In the event of diffusion of popular uprisings across countries, drawn observations cannot be considered separate entities, as outcomes in one country might affect outcomes in another. Furthermore, if the diffusion pattern follows Proposition 1, this interaction will grow as a function of the proximity between two countries. To produce unbiased estimates, it becomes crucial to incorporate spatial interactions in our case. Therefore, conventional multivariate methods are ruled out, as these cannot differentiate between relative locations and are subsequently unable to control for the complexity in the spatial interactions suggested by Proposition 1. This calls for developing our curriculum-based econometric toolbox, by searching for new theories and methods that can fill this void.

Fortunately, the concept of spatial interaction is theoretically formalized within the field of econometrics–for example by Anselin (2001, p. 310) as 'how the magnitude of a variable of interest … at a given location … is determined by the values of the same variable at other locations in the system'–and is known as spatial dependence. The academic field covering this topic, known as spatial econometrics, originated as a suggestion from Jean Paelnick in the 1970s, and Luc Anselin later formalized the concept from 1988 and onwards. To date, spatial econometrics is a well-recognized academic field that has come to encompass a range of empirical methods designed to control for and measure spatial dependence (Anselin, 2010). In the below exposition of spatial econometrics, we draw on the work of Anselin (1999; 2001; 2006) unless stated otherwise.

In essence, spatial dependence, also known as spatial autocorrelation, implies spatially correlated error terms if not controlled for. This can be seen as comparable to serial correlation in time series analysis, and violates the classical regression assumptions much in the same manner (Beardsley, et al., 2006). One of the main methods used to arrange and thereby restrict the components of the error structure is to model what is known as a 'spatial stochastic process', or 'spatial random field'. This represents a range of stochastic variables y, indexed by location i, formalized as

$$\{y_i, i \in D\} \tag{14}$$

In this process, each y is marked by location from a set of discrete connected entities or a continuous surface, denoted D. Spatial autocorrelation is now formalized as

$$cov[y_i, y_j] = E[y_i y_j] - E[y_i] \cdot E[y_j] \neq 0, for\ i \neq j \quad (15)$$

In other words, spatial autocorrelation exists when the outcomes of a random variable of interest, y, for two separate locations i, j are correlated. This expression can be extended to demonstrate the covariance between errors, as discussed earlier, simply by substituting y_i with ε_i in (14) and (15). As stated by Anselin (2001), it is the covariance expressed in (15) that becomes interesting when one can interpret a certain configuration of non-zero entity pairs in terms of spatial interaction. In our case this is implied from Proposition 1, as it suggests that popular uprisings diffuse into close countries.

Controlling for spatial autocorrelation requires modelling of the spatial random field's functional form. In other terms, it is necessary to map, on a priori basis, how the outcomes of certain variables at different locations are related to each other, in order to control for this dependence. This can be achieved by introducing a so-called spatial weights matrix, denoted W. This $N \times N$ positive matrix (where N is the number of locations) models the structure of the spatial random field. More specifically, it indicates what locations affect the outcome of each individual location in the system, and the magnitude of the effects stemming from these associations. The effect of a country on itself is by convention set to zero ($w_{ii} = 0$) (Fischer, et al., 2010). Consequently all diagonal elements are excluded in W. The matrix takes different forms due to how spatial interactions are modelled (which we will discuss more in depth later on), but for now it suffices to understand that W assigns weights according to how much entities affect each other.

Combining the spatial weights matrix with a dependent variable at location i, the so-called spatial lag operator is defined as

$$[Wy]_i = \sum_{j=1,\dots,N} w_{ij} y_j \quad (16)$$

or, formalized as a matrix,[19]

$$Wy \quad (17)$$

[19] (16) and (17) are strictly separate from (1) although their notations, derived from their original works, coincide.

This operator represents the weighted average of spillovers from each y onto associated entities. To understand the mechanism of this lag, for each y_i we further define a set of associated entities, S_i. It then follows that just corresponding y_j are contained in the lag, since the elements in the weights matrix only are non-zero for those $j \in S_i$, for every i. The concept of the spatial lag operator can be extended to the interacting of not only the dependent variable, but also of vectors such as the explanatory variables or the error term, with the weights matrix. Thus expression (17) is not limited to involving y, but can be generalized to that 'the spatial lag of a random vector *z* is … *Wz*.' (Anselin, 2006, p. 909)

The generalized spatial lag operator Wz has opened up for several specifications that incorporate spatial dependence in the estimation process. In standard linear regressions, there are two main approaches for this incorporation. Spatial error models (SEM) control for the spatial effect in the error term, while spatial autoregressive models (SAR) add an additional regressor in the form of a spatially lagged dependent variable (see (17)). Ideally SEM and SAR should be estimated simultaneously, but due to complications in the error model this is not possible (Lundberg, 2002).

SEM controls for spatial dependence in the error term, explicating how unexplained shocks to a dependent variable affect outcomes of the same variable in associated locations (Lundberg, 2002). It is analogous to a time series model with serially correlated errors, a comparison telling us that 'the only way that observations are interdependent is through unmeasured variables that are correlated, in this case across space.' (Beardsley, et al., 2006, p. 6) SEM corrects for this spatial bias and is defined as

$$y = X\beta + \varepsilon$$

where (18)

$$\varepsilon = \lambda W \varepsilon + u$$

and y is the dependent variable, X is a set of exogenous independent variables, ε is the vector of all errors, and u is the vector of idiosyncratic errors. Our parameter of interest is the coefficient of the spatial lag operator λ. The feasible range for λ is [-1,1] (Anselin, 2006). If λ equals zero, the weights matrix does not explain the spatial relationship that may exist (Aldstadt & Getis, 2010). In contrast, a value of λ close to one indicates that the weights matrix W correctly specifies the spatial relationship between unexplained factors and the dependent variable in associated locations.[20] Still, as no spatial lag operator is included as an explanatory variable in the specification, no substantive spatial dependence is measured (Anselin, 2001).

In contrast to SEM, the spatial autoregressive model assesses whether there exists a spatial interaction in the dependent variable and, if present, its implied strength (Anselin, 1999). This is a substantiveness unobtainable in SEM. SAR can be seen as analogous to a time series model with a lagged dependent variable. In SAR, the dependent variable is influenced by the weighted values of the outcomes of the same variable in associated locations. Unlike a time series autoregressive model where correlation due to time elapse only can move in one direction, the SAR model allows for potential spatial interactions to move in multiple directions (Dean & Leeson, 2009). This becomes crucial in our investigation, as we want to see how popular uprisings may flow in both directions between countries. To model SAR, the formerly discussed spatial lag operator for the dependent variable is included as a regressor in the simple linear regression model:

$$y = \rho W y + X\beta + \varepsilon \tag{19}$$

The same notations as before are used, but in this case ε is a vector of independent and identically distributed (IID) errors. In the assessment of SAR, focus lies on the coefficient of the spatial lag operator ρ, also known as the spatial autoregressive coefficient. This coefficient has the same properties as λ in SEM. If ρ is close to one, the weights matrix correctly specifies the true spatial interaction embedded in the dependent variable. On the other hand, a value close to zero implies that no spatial dependence as specified by the weights matrix can be found in the dependent variable.

SEM and SAR, as specified above, only allow for instantaneous spatial interactions within a certain time period. In theory, it is possible to specify a spatial lag operator that incorporates a time-lagged dependent variable. This yields a space-time dynamic SAR model, which allows for intertemporal spatial interactions (Anselin, 1999). In this study, due to limitations in our statistical software, we are restricted to instantaneous versions of the spatial models. Thus, if our proposed pattern of diffusion has an intertemporal dimension, the employed econometric models will not detect it.

Neither SEM nor SAR should be estimated using OLS. In the case of SEM, although OLS is consistent in the presence of spatial interaction, the reported standard errors will be misleading if

[20] A negative value of λ can be estimated as the corresponding positive value by changing the signs of the weights in the matrix.

λ is non-zero, making $\hat{\beta}$ inefficient (Beardsley, et al., 2006). For SAR, even with IID errors, OLS will suffer from endogeneity as the spatial lag operator is correlated with the error term. To address these problems, both SEM and SAR should be estimated using maximum likelihood (Anselin, 1999).[21] Furthermore, we run both models controlling for fixed effects.[22]

Spatial weights matrix

Revisiting the spatial weights matrix, we conclude that the structure of W is a model of the interactions within the true spatial field, enabling the assigning of weights for each location based on its association to other locations. Consequently, to be able to estimate the actual spatial dependence using SAR or SEM, it is crucial that we can properly specify the unobserved interaction pattern (Aldstadt & Getis, 2010).

Adding to the definition of the spatial weights matrix, its elements need to be non-stochastic and exogenous to the model (Anselin, 1999). Despite extensive theoretical work on spatial weights specification, only a limited scope of practical guidance is available for choosing 'suitable' weights for a given case (Anselin, 2006). This sheds light on the certain degree of arbitrariness involved in functional form specification of a spatial random field (Aldstadt & Getis, 2010), an apparent drawback of spatial econometrics. As no previous work states how popular uprisings diffuse across countries, this problem becomes apparent in our field of study. Nevertheless, as concluded by Griffith (1996, p. 80) '[i]t is better to posit some reasonable geographic weights matrix specification than to assume all entries are zero.'

We specify our spatial weights matrix based on Proposition 1: the closer two countries are, as measured by c, the easier it becomes for a popular uprising in one of the countries to diffuse to the other. The parameter c is a measure of cultural, political, geographical, and economic closeness of countries. Ideally, the unique elements of each measure of closeness should be incorporated separately through different weight matrices in the model. However, in practice, this approach encounters two main complications. First, drawing on the reasoning of Anselin (2006), one does not want to include potentially highly correlated measures separately, since their linkages in the weights matrices may be overlapping. Second, the suggested measures other than

---

[21] More on maximum likelihood estimation for spatial models is found in Anselin (2006, pp. 922-927).

[22] Ideally, we would like to use the Hausman test to determine whether the fixed effects or random effects estimator is preferable. However, as we use simulated data, the Hausman test is not applicable in our econometric software. Instead, we present our results using the random effects estimator in Appendix D to enable a descriptive comparison with our main results using the fixed effects estimator. The random effects regressions render estimates much alike the fixed effects results, both in regard to size and significance. Therefore, our discussion of results is limited in scope to the fixed effects estimator.

geography are prone to change over time. This violates the assumptions of the fixed nature of the weights matrix. In this sense, as Anselin (1999) states, geography represents an appealing basis for specification due to its exogeneity. Naturally, also geography is time-variant, but usually not to the same extent as the other measures. In light of this complication, we choose to not include one weights matrix for each measure in c.

Given that geographical closeness presumably is highly correlated with the other measures of closeness, we opt for the former as a proxy for c. One of the advantages of using geographical distance as a proxy is the lower degree of arbitrariness involved in measuring distance compared to the other types of closeness. In this sense, geography-based measures represent good proxy variables for closeness, and one may further, on logical grounds, assume that geographical proximity influences the cultural, political, and economic components of c rather than the other way around. With geographical distance as a proxy for c, Proposition 1 specifies a weights matrix where the closer two countries are geographically, the larger weight they are assigned. We operationalize this through two forms of weights matrices: contiguity and inverse distance.

The contiguity matrix is one of the more frequently used spatial weights matrices (Anselin, 2006). We set the weights binary, such that each country pair sharing a common border is given a weight equal to unity. This results in a symmetric matrix, as $w_{ij} = w_{ji}$, where popular uprisings only affect revolutionary activity in first-order contiguous countries.[23] In addition to this matrix, we define two higher-order contiguity matrices: second-order and third-order contiguity. Second-order contiguous countries are separated by one country, whereas third-order contiguous countries are separated by two countries. Apart from their differing association patterns, these higher-order matrices also assign binary weights.

A more nuanced specification of W is a continuous weights matrix based on the distance between countries. To model the matrix so that it is in line with Proposition 1, the weights must decrease with increasing distance. This is achieved by defining the weights of the matrix as the inverted distance between countries. The inverse distance form allows for spillovers not only from bordering countries, but from all locations included in the set. In comparison to the first-order contiguity form, the inverse distance matrix is more compatible with Proposition 1, as our model does not restrict the interaction to contiguous countries. Still, we find it valuable to include the contiguity form as a simple and perhaps underspecified weights matrix (few countries

[23] It is possible to have different origin- and destination-based weights, formalized as $w_{ij} \neq w_{ji}$ (Fischer, et al., 2010), but as Proposition 1 makes no such distinction, the weights matrix is set symmetrical.

modelled as close) since it provides a modest reference case in our empirical analysis (Griffith, 1996).

A common practice is to row-standardize complete weights matrices. The row-standardized weights are given by $w_{ij}^{s} = \frac{w_{ij}}{\sum_j w_{ij}}$ (Anselin, 2006, p. 909). In the case of first-order contiguity, this means that if a country shares borders with two nations, each of these are assigned the weight 0.5 in the matrix. According to Getis and Aldstadt (2010) there are findings both in favour and against this procedure, but it is usually considered a convenient practice. Furthermore, as Beck et al. (2006) point out, by standardizing we do not have to worry about in what units we measure closeness, and the metric of the spatial lag operator will be the same as for the dependent variable. Based on these findings we choose to row-standardize the contiguity and inverse distance matrices.

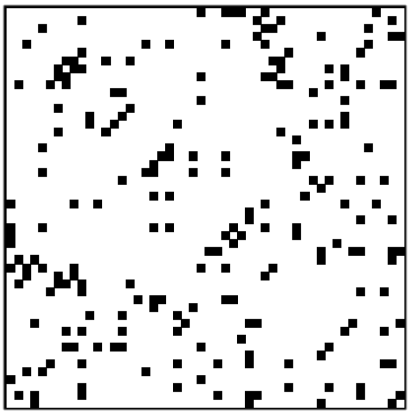
Data and variables selection

To measure spatial dependence of popular uprisings across countries, we construct a panel of protest and riot counts for the African countries between 1997 and 2013. The data is collected from Armed Conflict Location & Event Data Project (Clionadh, et al., 2010), containing 79,000 geolocated events, from which we detach observations categorized as protests and riots directed against government institutions, obtaining 17,050 event observations. We aggregate the observations to monthly, quarterly, and yearly counts for each nation in Africa. Thereby, we assume that transnational diffusion patterns, if they exist, are apparent in time spans from one month to one year. This aggregation approach follows due to the lack of formal guidelines on how to temporally aggregate data when using instantaneous spatial models. The three aggregates serve as our dependent variables, and indicate the level of popular uprisings in a country for a certain time period.

In specifying the contiguity weights matrices, we use Google Maps (Google, 2014) to identify bordering African countries. As weights matrices preferably should not include any islands (Viton, 2010), Madagascar is set to border Mozambique.[24] The distance between African countries, entering into the inverse distance matrix, is calculated based on country centroids, with coordinates obtained from the CIA World Factbook (Central Intelligence Agency, 2014). For both the contiguity and inverse distance matrices, we include South Sudan as a separate country while Western Sahara, being on the United Nations list of non-self-governing territories (United

[24] As a robustness test, we also perform our analysis using a contiguity matrix where Madagascar is set to have no bordering countries. The estimation results from this test are similar to those presented later in this study.

Nations, 2014), is considered to be a part of Morocco.[25] The first-order contiguity and inverse distance matrices, before row-standardization, are presented in Figure 8.



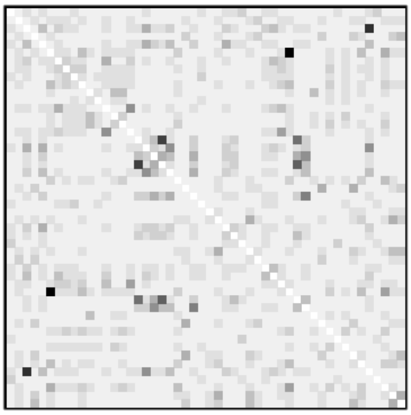


Figure 8: Non-standardized weights matrices using first-order contiguity (left) and inverse distance (right) for Africa. Darker spots indicate contiguous or geographically close country pairs.

The control variables used in the spatial regressions are based on theories explaining the occurrence of revolution. Due to the large amount of theories on this topic, we use Goldstone's (1980) categorization of theories of revolution as guidance in order to avoid missing any important explanatory factors. The three categories, together with their respective theories, are described in the section covering previous research. In the below discussion we focus on operationalizing the different theories of revolution for empirical use. Unless otherwise stated, the data for the control variables is collected from the World Bank (2014).

We control for the frustration-aggression category by including the J-curve theory and Gurr's (1968) four influences on frustration. In operationalizing the J-curve for both economic and political considerations, we follow the precedent provided by Knutsen (2014) in introducing a dummy that equals unity if a country experiences a period of improvement followed by a sharp reversal. The economic J-curve dummy is defined as two consecutive years of above-average growth in real GDP per capita (2.13 per cent), followed by a year of real GDP per capita growth that deviates by at least one standard deviation below the average growth rate. We base the two year period of growth on the average length of expansions in business cycles in Africa (Male, 2011, p. 25). The political J-curve dummy is defined for a three year period of positive development in the Polity index, followed by a fall of two index scores–equivalent to one

[25] South Sudan gained independence in 2011. Most variables prior to this year are simulated for the country (see later reasoning). The sovereignty of Western Sahara is disputed, but as the country is under the control of Morocco, we classify it as a part of the latter (Nationalencyklopedin, 2014).

standard deviation below the average yearly change in the index–during a single year.[26] The Polity index captures 'authority characteristics of states' and is retrieved from the Polity IV Project (2011). In line with Freund and Jaud's (2014) empirical study of rapid political change, we set the length of the political improvement phase to three years.

Gurr's (1968) operationalization of his own theory consists of creating complex and somewhat arbitrary indices of the four influences based on an array of measures. Following the scientific principle of parsimony, we opt for a simpler approach. The two influences coercion and institutionalisation are controlled for by including the Polity score, under the assumption that countries with low scores (autocracies) are more likely to use coercive measures and to have poor institutional qualities than countries with high scores (democracies). To control for facilitation, we follow the reasoning of Gurr (1968) in saying that past levels of civil unrest indicate the presence of factors facilitating revolutionary activity. We therefore include a lagged dependent variable of one time period. In addition, previous levels of popular uprisings, as captured by the lag, suggest how legitimate the regime is perceived to be, which is the final influence mentioned by Gurr. We also include the Gini coefficient, a measure of income inequality, as an indicator of governments' propensity to engage in systematic closures of economic opportunities, which may risk its legitimacy (Lichbach, 1989).

In controlling for the structural-functionalist category, we include dummies for rapid change in the factors that, according to Stone (1966), can bring society into dysfunction. As rapid change in economic factors probably is strongly correlated to technological change, we cover these two factors using a single variable with the intention to avoid multicollinearity.[27] For this purpose, we use a dummy for years where countries have experienced a three year growth rate in the information and communication technology (ICT) development index above 32.2 percent, equivalent to one standard deviation above the average three year growth rate in the index (International Telecommunication Union, 2013). We do not include Stone's (1966) remaining factors, imperial conquest and new metaphysical beliefs, as we cannot operationalize these in a reliable manner. Lastly, to control for countries' exposure to international economic pressures, we include a measure of openness to international trade. In doing so, we follow the precedent of Bates (2000) by using the level values of imports and exports as a percentage of GDP.

[26] Both the economic and political J-curves are based on relative measures from our sample. Therefore, these variables can only be meaningfully applied to our specific data set. This restriction also applies to the following control variables operationalized based on relative measures.
[27] In our sample, the correlation between real GDP per capita and ICT is 0.821.

The interest group conflict category is included in our specification by controlling for situations where the two preconditions for revolution can arise: first, a failure of the political institutions to mediate in conflicts and, second, that several interest groups have the necessary resources to use violence in achieving their goals. Goldstone (1980) notes that interstate war, economic conditions, and urbanization, amongst other factors, can result in new interest groups and shift the allocation of resources. Following Knutsen (2014), we control for if a country has been engaged in interstate war during the current or two previous years, using data from Correlates of War (Reid Sarkees & Whelon Wayman, 2010). In the absence of any previous operationalization of economic conditions or urbanization in the context of the interest group conflict category, we choose to create an interaction term. It is defined as the real GDP per capita level for countries with Polity scores below six, categorized as non-democracies (Gurr, et al., 2011). The interaction term directly captures the economic conditions, but also indirectly the level of urbanization, as GDP per capita and urbanization presumably are highly correlated. By limiting the measure to non-democracies, we attempt to fulfil the first precondition by arguing that the political institutions of non-democracies are poorer at resolving interest group conflicts than those of democracies. That is, we expect to see a larger effect of real GDP per capita on protests and riots in non-democracies. Lastly, in order to get a saturated regression, we include the level of real GDP per capita without any interaction.

In addition to the above control variables based on theories of revolution, we want to control for any potential biases in the structure of our data of protests and riots. ACLED (2010) claims that the

> [r]ecorded increases in conflict event levels correspond in part to increased digitisation of media sources, access and coverage of conflict and human rights violations by civil society and international organisations from which event data is drawn, and improvements in data collection and coding within the ACLED project. … From 1997-2013, riots and protests have witnessed the sharpest absolute and proportional increase.

To adjust for this upward trend in observations, partly due to refinements of the data collection process, we introduce time dummies. A further motive behind this introduction is to control for time fixed effects in the level of popular uprisings. For monthly and quarterly regressions we include year fixed effects. However, due to complications with our statistical software, we are only able to include dummies for two-year periods in our regressions on yearly aggregated data.

Fixed effects estimation requires serially uncorrelated idiosyncratic errors, otherwise the standard errors become biased (Wooldridge, 2013; Drukker, 2003). Wooldridge (2013) warns about the dangers of serially correlated errors when including time-lagged dependent variables. As we include previous levels of popular uprisings, we would ideally like to test for serial correlation in our panel data model. However, no such function is provided with the spatial econometrics applications in our statistical software. Instead, we adjust the standard errors for within country serial correlation in the idiosyncratic errors.

Conducting spatial estimation requires a strongly balanced data panel. That is, there may be no missing values in the data set. As our data lacks values on certain explanatory variables–especially for monthly and quarterly aggregates as we mainly have year-level data–we are required to simulate the missing values in order to proceed in the estimation process. We choose to do this using a multiple imputations (MI) approach, as it is compatible with SAR and SEM models (Han & Lee, 2013). Multiple imputations analysis consists of three steps. The first step is to formulate an imputation model and, based on it, simulate several imputations for each missing value. We acknowledge the risks associated with misspecifying the imputation model, which may give rise to biased results (StataCorp, 2013). However, as we do not believe that the results will be more reliable if we drop large parts of our data, we deem multiple imputations to be the preferred approach. The second step involves analysing the new values to evaluate the validity of the imputations. Lastly, all imputations are merged, and are thereafter ready to be used in the main regression of interest (UCLA: Statistical Consulting Group, 2014).

Before advancing with the simulation we make an adjustment to the data set. As none of our independent variables contain values for year 2013 we decide to drop this year from our sample, as a first step towards a strongly balanced data panel. Despite the loss of observations, by dropping these entries we believe that we make more accurate estimations, based on the reasoning that we otherwise are required to rely on purely simulated explanatory data for one of the 17 years observed.

Revisiting MI, the first step in specifying an imputation model is to define the properties of the missing data. In our case observations are missing at random, why we use a multivariate regression model to impute values. When specifying such a regression, one wants to include what is known as auxiliary variables.[28] These are explanatory variables that are not part of the main

[28] Ideally, we would like to include the independent variables of our main regression that do not contain any missing values as well as cluster dummies for the countries in our imputation model. However, as the inclusion of these gives

regression and contain no missing values. In our case, we choose to include total population, urbanization, infant mortality rate, and fertility rate as auxiliary variables in our simulation model. Furthermore, the dependent variable shall also be controlled for in the simulation regression. Using this regression, the imputations are then produced by methods simulating random values from non-standard distributions. We use the simulation methods Markov Chain Monte Carlo (MCMC) for continuous variables and Multiple Imputation by Chained Equations (MICE) for our discrete and binary variables. In accordance with common practice, we simulate 20 sets of imputed values (StataCorp, 2013).

Before using the imputed data set in our main regression we evaluate the validity of our simulations. As there exists no general test for this purpose we follow the suggestions of UCLA: Statistical Consulting Group (2014) and compare, for all variables, the sample mean of the observed values with the mean of the imputed values in each of the 20 simulations. We cannot determine whether the observed or simulated mean is closer to the population mean. What we can examine, however, is how much the simulated means deviate from the observed mean, as well as if the simulated means fall within the defined range of each variable. We keep any variable with a mean within the defined variable range. Although MCMC generates extreme values, all simulated variables meet this criterion, why none of them are dropped. The observed and simulated means, along with their corresponding minimum and maximum values, are presented for each imputed variable and time period in Appendix E.

It should be noted that we only have access to yearly data for the control variables, and we are therefore required to impute data for quarterly and monthly observations. Thus, the yearly regressions produce more reliable results as they depend on fewer imputations than quarterly and monthly regressions. The latter regressions should be viewed as complements used to uncover if the diffusion pattern is more apparent in shorter time spans.

Hypotheses

As described previously, we have specified the first-order contiguity and inverse distance matrices in accordance with Proposition 1. The spatial autoregressive coefficient ρ in SAR shows how well a weights matrix specification captures potential spatial relationships in our sample of protests and riots. With a ρ equal to zero there is no spatial relationship in the sample as specified by the weights matrix. Contrary, if a spatial autoregressive coefficient equals one, the weights

rise to '[t]he issue of perfect prediction during imputation of categorical data' (StataCorp, 2013, p. 118) in our case, we have to rely solely on auxiliary variables and the dependent variable.

matrix specification perfectly captures the sample's spatial relationship. To test Proposition 1, and thereby also the notion that there exists a diffusion of popular uprisings across countries, we formulate the following hypotheses:

$$\text{H0: } \rho = 0$$

$$\text{H1: } \rho \neq 0$$

Intuitively, a statistically significant and non-zero ρ can have two interpretations. In case of $\rho > 0$, popular uprisings tend to spill over to close countries. A negative estimate on the other hand indicates that uprisings in a country tend to be at the expense of close countries' uprisings.

We include SEM to further investigate the spatial relationships across countries. SEM captures how the level of popular uprising in a country is affected by unexplained shocks to revolutionary activity in close countries. Although lacking a substantive interpretation related to Proposition 1 and the diffusion of popular uprisings, SEM may provide additional support for the spatial linkages potentially found using SAR. We therefore formulate corresponding hypotheses for SEM:

$$\text{H0: } \lambda = 0$$

$$\text{H1: } \lambda \neq 0$$

Given the relatively large size of our data set, we test the hypotheses for SAR and SEM at the 1 per cent significance level. If the null hypotheses can be rejected at this level, we cannot exclude the possibility that the tested weights matrices correctly specify at least some of the spatial dependence in the underlying population of protests and riots directed against government institutions.

As a final test of the transnational diffusion of popular uprisings, we run SAR and SEM for second- and third-order contiguity matrices. If we see a negative trend in ρ and λ as we move to higher-order contiguity matrices, it implies that the diffusion of popular uprisings declines with increased distance between countries. This would provide support for the pattern of diffusion suggested by Proposition 1.

Results

The main results of our empirical analysis are presented in Table 1. The table displays the estimates of ρ and λ from SAR and SEM, respectively, for each weights matrix. The inverse distance form represents our base case, as it is most compatible with Proposition 1, and is compared with the more modest contiguity form. In accordance with our choice of aggregation of the dependent variable, the results are also presented for monthly, quarterly, and yearly time intervals. The yearly regressions should be seen as providing the most reliable results, as they contain fewer imputed values for the control variables. As our interest lies in analysing spatial dependence, we focus on the spatial coefficients for SAR and SEM in the results presented in this section, and in particular on ρ as it indicates the substantive diffusion of popular uprisings.

Before advancing to our main results, we want to comment briefly upon the estimated coefficients of the control variables.[29] All control variables except Polity have signs that are in accordance with the theoretical predictions. Some variables that we would expect to have an economically large impact, such as GDP per capita, turn out to have a quite small effect on the number of protests and riots. Furthermore, there seems to be a trend of increasing statistical significance of estimates for shorter time spans, which probably is due to the larger number of observations in monthly and quarterly data.

Inspection of Table 1 reveals that SAR and SEM produce statistically insignificant spatial coefficients, with both positive and negative estimates between -0.134 and 0.031. Setting the statistical insignificance aside momentarily, we comment on the economic scope of the results. The positive coefficient in SAR of 0.031 predicts that a country in our sample 'catches' 3.1 per cent of the popular uprisings in close countries for the same time period. Conversely, the ρ of -0.134 predicts that the number of popular uprisings in a country is lowered by 13.4 per cent of the popular uprisings in close countries for the same time period. Negative estimates do not accord with the diffusion pattern suggested by Proposition 1. Interestingly, the inverse distance matrix renders estimates below zero in all cases but one, while its contiguity counterpart solely produces positive values. This may suggest the presence of a negative spatial tendency beyond the first-order contiguous countries. As for SAR and SEM, they render fairly similar estimates on average, although the λ estimates for the quarterly and monthly aggregates of the inverse distance matrix exceed their ρ equivalents. In the same manner, the estimates do not differ substantially

[29] Complete regression output is provided in Appendix G.

when changing time aggregation, which indicates that instantaneous spatial interactions are similar for the different time intervals.

In assessing the magnitude of the coefficients, we compare our estimates with the results from other spatial econometric studies of social science phenomena. Typically, spatial autoregressive coefficients range from 0.05 to 0.15, with high values peaking at around 0.3 (Dean & Leeson, 2009; Dean, et al., 2012; Lundberg, 2002). In light of this, our estimates seem fairly modest in size.

Table 1: Estimates of ρ and λ using fixed effects

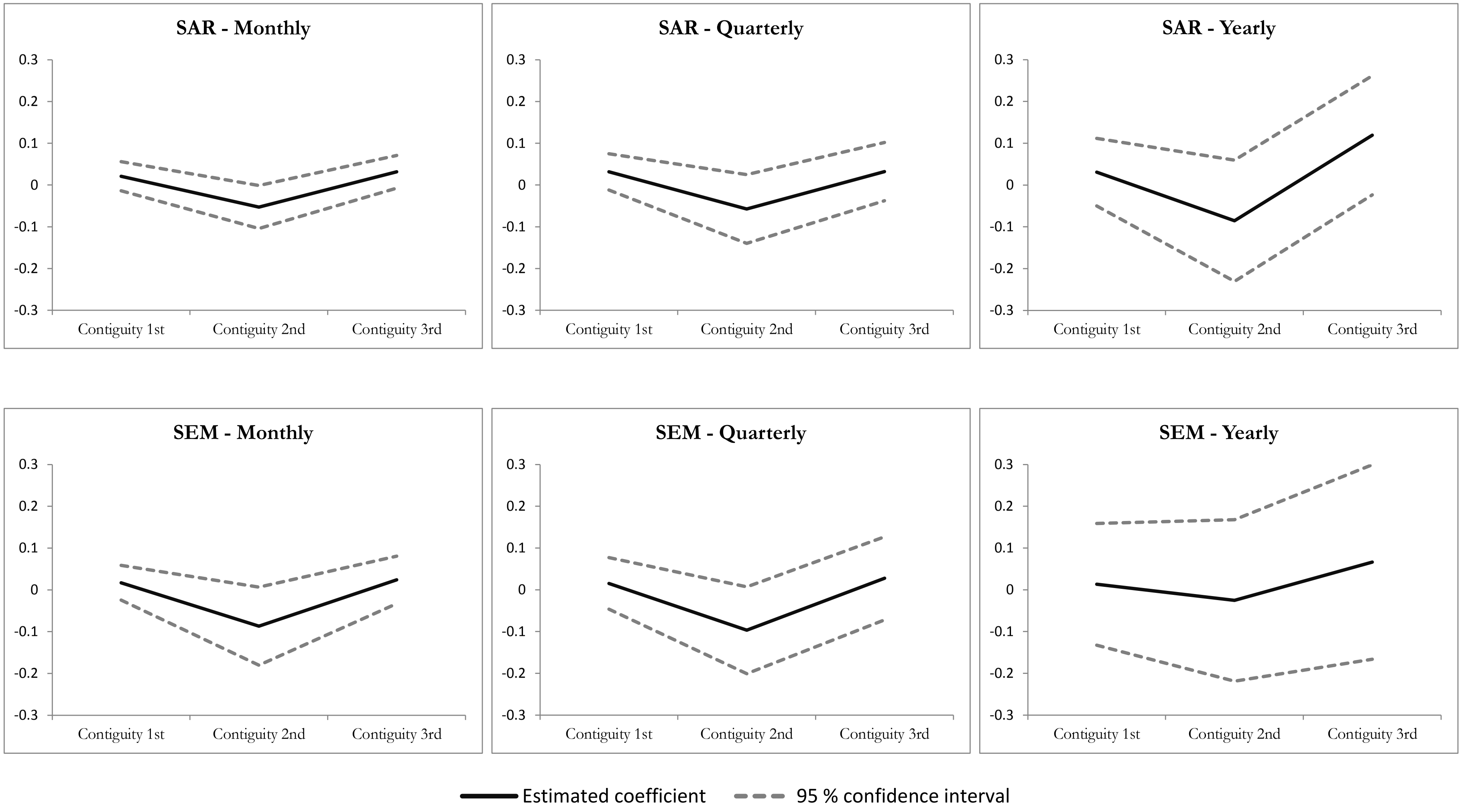
	ρ (SAR)		λ (SEM)	
	Inverse distance matrix	Contiguity matrix	Inverse distance matrix	Contiguity matrix
Monthly (n=50, t=192)	-0.025 (0.049)	0.021 (0.018)	-0.100 (0.089)	0.017 (0.021)
Quarterly (n=50, t=64)	-0.027 (0.070)	0.031 (0.022)	-0.134 (0.101)	0.015 (0.031)
Yearly (n=50, t=16)	0.029 (0.092)	0.031 (0.041)	-0.034 (0.215)	0.013 (0.072)

Note: *, ** and *** denote significance at the 10, 5 and 1 per cent level, respectively. Robust standard errors are presented in parenthesis. SAR is performed with a lagged dependent variable of one period, while SEM, for reasons of tractability, is implemented without a lagged dependent variable. Monthly and quarterly regressions are performed with year dummies, while yearly regressions include time dummies for two-year periods.

Returning to statistical significance, we observe that none of the estimated coefficients are significant, even at a 10 per cent level. Consequently we cannot reject the null hypotheses that the coefficients ρ and λ are equal to zero. This implies that our specified spatial weights matrices perform poorly in capturing the underlying, if existing, spatial dependence in our data.

As a final investigation of the pattern of diffusion suggested by Proposition 1, we run SAR for higher-order contiguity matrices and compare their results with the corresponding estimates of the first-order contiguity matrix. The results are graphed in Figure 9, where the dotted lines represent the 95 per cent confidence interval for each estimate. Studying the figures, we observe convex trends for each graph, where first- and third-order contiguity estimates are positive, with negative coefficients in between. Interestingly, we obtain increased statistical significance for second-order contiguity matrix estimates. These results do not present any evidence in favour of Proposition 1, as we then would expect to see a negative trend in the coefficient estimates.

Altogether, we fail to reject our null hypotheses for both SAR and SEM at the 1 per cent level in all of our cases. The spatial weights matrices, specified in accordance with the pattern of diffusion suggested by Proposition 1, thus perform poorly in explaining any potential underlying spatial relations. Accordingly, we do not find any empirical support for instantaneous diffusion of popular uprisings across African countries in any of the time intervals investigated.



Note: The spatial coefficients using the second-order contiguity matrix are statistically significant at the 10 per cent level for the monthly SAR and SEM models and the quarterly SEM model. All other spatial coefficients are insignificant at that level.

Figure 9: Fixed effects estimates of ρ and λ for first-, second- and third-order contiguity matrices.

Conclusions

In this thesis, we set out with the purpose of examining whether there exists a diffusion of popular uprisings across countries. As a first step in this process we develop a model explaining how a potential transnational spread of uprisings might occur. The model proposes that an increased level of cultural, political, geographical, and economic closeness of countries facilitates diffusion. To empirically test the presence of such a diffusion pattern, we apply spatial econometric methods to a dataset containing protests and riots directed against government institutions in African states during 1997-2012. The predicted pattern of diffusion provided by our model is included in the econometric specification by using geographical distance between countries as a proxy for the four measures of closeness.

The empirical results are unambiguous. The spatial lag coefficients, indicating the presence of instantaneous transnational diffusion of popular uprisings, are insignificant. This applies both to specifications where we examine strictly contiguous countries, as well as when we allow for spatial interactions across greater distances. Furthermore, we do not observe a more modest spread when moving from first-order to higher-order contiguous countries, which contradicts the pattern of diffusion proposed by our model. In brief, based on the results of our study, we find no evidence supporting the existence of a diffusion of popular uprisings across African countries during our period of study.

In assessing the accuracy of our findings, we highlight the limitations of the study. These concerns are also intended to serve as a *terminus a quo* for future research. First, our dataset of protests and riots contains 17,050 observations, some of which can be considered quite minor events.[30] Our study thus captures events that are far from the large-scale and focused uprisings witnessed during the Arab Spring. It might be the case that popular uprisings need to be sizeable in order to diffuse. If so, our dataset presumably contains noise that inhibits observation of any spatial linkages.

Second, the pattern of diffusion proposed by our model may be incorrect. Popular uprisings can diffuse through other linkages, in which case our weights matrices fail to detect it. Furthermore, in operationalizing the proposition for our weights matrices, we use geographical distance as a proxy for the other types of closeness. We cannot disqualify the possibility that another measure of closeness would constitute a more suitable proxy.

[30] For example, one of our observations for South Africa contains the event description 'Parents and community members protest to call for removal of unpopular teacher at school.'

Third, as we only investigate instantaneous diffusion of popular uprisings within certain time periods (month, quarter, and year), we are unable to detect any diffusion pattern with an intertemporal dimension. As stated earlier, we would prefer to include a time-space dynamic model to test for this. Unfortunately, the statistical software we use does not support this function.

Fourth, our empirical analysis relies on simulated control variables. According to UCLA: Statistical Consulting Group (2014), it is difficult to assess the validity of imputed values. Although the simulations seem reasonable, we cannot dismiss the risk that they bias our estimation results.

Finally, given that our empirical analysis only considers data from Africa for a relatively short time span, we acknowledge the limited generalizability of our results. In addition to addressing the concerns mentioned above, future research can beneficially be applied to other regions and time periods in order to study the external validity of our findings. A better understanding of the claimed transnational linkages of political unrest would be valuable for policymakers and the business community alike. As for the contribution of this thesis, we find no evidence supporting the notion that popular uprisings diffuse across countries.

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Appendix

Appendix A

This property is proved by setting $V^i\left(y^i = 0\middle|x^i\right) = V^i\left(y^i = 1\middle|x^i\right)$ and then implicitly differentiating x^i with regards to O^e

$$\frac{\partial}{\partial O^e}\left(V^i\left(y^i = 0\middle|x^i\right)\right) = \frac{\partial}{\partial O^e}\left(V^i\left(y^i = 1\middle|x^i\right)\right)$$

$$\frac{\partial}{\partial O^e}\left(f(1 - O^e), \theta(t)\right) + \frac{\partial N\left(1 - x^i\right)}{\partial x^i} * \frac{\partial x^i}{\partial O^e} = \frac{\partial}{\partial O^e}\left(F\left(O^e, \theta(t)\right)\right) + \frac{\partial N\left(x^i\right)}{\partial x^i} * \frac{\partial x^i}{\partial O^e}$$

$$\frac{\partial x^i}{\partial O^e} = \frac{\frac{\partial F\left(O^e, \theta(t)\right)}{\partial O^e} - \frac{\partial f\left(1 - O^e, \theta(t)\right)}{\partial O^e}}{\frac{\partial N(1 - x^i)}{\partial x^i} - \frac{\partial N(x^i)}{\partial x^i}}$$

Following from the properties described in relation to (3) and (4), the numerator will always be positive and the denominator will always be negative, giving that $\frac{\partial x^i}{\partial O^e} < 0$.

Appendix B

(12) and (13) are derived by solving the differential equations (10) and (11):

$$\frac{\partial P(t)}{\partial t} = -(\omega P(t) + \gamma)(P(t) - 1)$$

$$\leftrightarrow \int -\frac{\frac{\partial P(t)}{\partial t}}{(\omega P(t) + \gamma)(P(t) - 1)}\, dt = \int 1\, dt$$

$$\leftrightarrow \frac{\ln(\omega P(t) + \gamma) - \ln(P(t) - 1)}{\omega + \gamma} = t + C$$

$$\leftrightarrow \frac{(\omega P(t) + \gamma)}{(P(t) - 1)} = e^{(t+C)(\omega+\gamma)}$$

$$\leftrightarrow P(t) = \frac{\gamma + e^{(t+C)(\omega+\gamma)}}{e^{(t+C)(\omega+\gamma)} - \omega}$$

Using the initial condition $P(0) = 0$ to determine the constant C

$$P(0) = \frac{\gamma + e^{C(\omega+\gamma)}}{e^{C(\omega+\gamma)} - \omega} = 0$$

$$\leftrightarrow \ln\left(e^{C(\omega+\gamma)}\right) = \ln(-\gamma)$$

$$\leftrightarrow C = \frac{\ln(-\gamma)}{(\omega+\gamma)}$$

By inserting the expression of the constant C into $P(t)$ we get

$$P(t) = \frac{\gamma + e^{\left(t+\frac{\ln(-\gamma)}{(\omega+\gamma)}\right)(\omega+\gamma)}}{e^{\left(t+\frac{\ln(-\gamma)}{(\omega+\gamma)}\right)(\omega+\gamma)} - \omega} = \frac{\gamma + e^{\ln(-\gamma)+t(\omega+\gamma)}}{e^{\ln(-\gamma)+t(\omega+\gamma)} - \omega} = \frac{\gamma + e^{\ln(-\gamma)}e^{t(\omega+\gamma)}}{e^{\ln(-\gamma)}e^{t(\omega+\gamma)} - \omega} = \frac{\gamma - \gamma e^{t(\omega+\gamma)}}{-\gamma e^{t(\omega+\gamma)} - \omega}$$

$$= \frac{1 - \frac{1}{e^{t(\omega+\gamma)}}}{1 + \frac{\omega}{\gamma e^{t(\omega+\gamma)}}} = \frac{1 - e^{-t(\omega+\gamma)}}{1 + \frac{\omega}{\gamma}e^{-t(\omega+\gamma)}}$$

Appendix C

This property is proved by setting $V^i\left(y^i = 0\middle|x^i\right) = V^i\left(y^i = 1\middle|x^i\right)$ and then implicitly differentiating x^i with regards to $\theta(t)$

$$\frac{\partial}{\partial\theta(t)}\left(V^i\left(y^i = 0\middle|x^i\right)\right) = \frac{\partial}{\partial\theta(t)}\left(V^i\left(y^i = 1\middle|x^i\right)\right)$$

$$\frac{\partial}{\partial\theta(t)}\left(f\left(1 - O^e, \theta(t)\right)\right) + \frac{\partial N\left(1 - x^i\right)}{\partial x^i} * \frac{\partial x^i}{\partial\theta(t)} = \frac{\partial}{\partial\theta(t)}\left(F\left(O^e, \theta(t)\right)\right) + \frac{\partial N\left(x^i\right)}{\partial x^i} * \frac{\partial x^i}{\partial\theta(t)}$$

$$\frac{\partial x^i}{\partial\theta(t)} = \frac{\frac{\partial F\left(O^e, \theta(t)\right)}{\partial\theta(t)} - \frac{\partial f\left(1 - O^e, \theta(t)\right)}{\partial\theta(t)}}{\frac{\partial N(1 - x^i)}{\partial x^i} - \frac{\partial N(x^i)}{\partial x^i}}$$

Following from the properties described in relation to (3) and (4), the numerator will always be positive and the denominator will always be negative, giving that $\frac{\partial x^i}{\partial\theta(t)} < 0$.

Appendix D

Estimates of ρ and λ using random effects

	ρ (SAR)		λ (SEM)	
	Inverse distance matrix	Contiguity matrix	Inverse distance matrix	Contiguity matrix
Monthly (n=50, t=192)	-0.033 (0.062)	0.024 (0.024)	-0.076 (0.082)	0.021 (0.022)
Quarterly (n=50, t=64)	-0.037 (0.053)	0.035 (0.036)	-0.117 (0.097)	0.022 (0.031)
Yearly (n=50, t=16)	-0.044 (0.103)	0.023 (0.040)	-0.054 (0.218)	0.011 (0.073)

Note: *, ** and *** denote significance at the 10, 5 and 1 per cent level, respectively. Robust standard errors are presented in parenthesis. SAR is performed with a lagged dependent variable of one period, while SEM, for reasons of tractability, is implemented without a lagged dependent variable. Monthly and quarterly regressions are performed with year dummies, while yearly regressions include time dummies for two-year periods.

Appendix E

Descriptive statistics of variables

Variable	Obs	Mean	SD	Min	Max	Unit
Protests	800	14.185	45.049	0	994	Count
J-curve political	780	0.005	0.071	0	1	Binary
J-curve GDP/capita	757	0.012	0.108	0	1	Binary
Polity	782	0.633	5.138	-9	10	Index
Gini	93	43.287	7.512	29.83	67.4	Index
ICT growth	81	0.160	0.369	0	1	Binary
International trade	745	74.639	36.290	17.859	275.232	% of GDP
Interstate war	800	0.013	0.111	0	1	Binary
Real GDP per capita	758	1932.995	4027.588	101.776	27136.09	USD (2005)
Real GDP per capita * Autocracy	755	1011.29	2047.147	0	14901.35	USD (2005)

Appendix F

Simulations monthly data set

	Observed value	Simulations m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10	m=11	m=12	m=13	m=14	m=15	m=16	m=17	m=18	m=19	m=20
J-curve political	0.005	0.005	0.005	0.005	0.005	0.005	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
J-curve GDP/capita	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.013	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012	0.012	0.012	0.012	0.013
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Polity	0.633	0.643	0.475	0.789	**0.806**	0.719	0.684	**0.436**	**0.913**	**0.812**	0.586	0.633	0.511	0.574	0.731	0.761	0.68	0.664	0.578	0.597	0.583
	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]
Gini	43.287	43.149	43.033	43.344	44.561	43.859	43.629	43.162	43.224	42.048	43.882	43.399	43.686	43.793	42.607	44.449	43.603	43.975	44.276	44.987	44.645
	[30,67]	[16,71]	[13, 100]	[17, 137]	[16, 140]	[15, 113]	[13, 124]	[16,90]	[17,89]	[16,76]	[18, 126]	[9,161]	[15, 119]	[14,73]	[12,88]	[11, 128]	[13, 102]	[19,85]	[13, 128]	[13, 102]	[18, 118]
ICT growth	0.16	0.123	**0.101**	**0.104**	**0.109**	**0.113**	**0.11**	**0.099**	**0.104**	**0.096**	**0.114**	**0.109**	**0.117**	**0.115**	**0.107**	**0.1**	**0.119**	**0.093**	**0.119**	**0.102**	**0.107**
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
International trade (% of GDP)	74.639	75.807	74.839	74.187	74.337	74.258	75.194	74.376	75.41	74.73	74.106	74.388	74.274	74.38	74.281	75.654	75.098	75.232	74.286	75.031	75.37
	[18, 275]	[-64, 275]	[-57, 275]	[-60, 275]	[-55, 275]	[-77, 275]	[-58, 275]	[-77, 275]	[-88, 275]	[-83, 275]	[-59, 275]	[-78, 275]	[-72, 275]	[-96, 275]	[-39, 275]	[-71, 275]	[-49, 275]	[-56, 275]	[-55, 275]	[-50, 275]	[-60, 275]
GDP per capita	1932.995	1881.338	1951.088	1882.265	1918.268	1788.861	1840.493	1891.768	1802.136	1957.251	1775.709	1893.861	1845.494	1732.502	1961.596	1852.76	1972.551	2039.917	1900.649	1890.765	1926.474
	[102, 27136]	[-10819, 27136]	[-11790, 27136]	[-11425, 27136]	[-12390, 27136]	[-10754, 27136]	[-11324, 27136]	[-13488, 27136]	[-10645, 27136]	[-12015, 27136]	[-12335, 27136]	[-12495, 27136]	[-12164, 27136]	[-12237, 27136]	[-13298, 27136]	[-11002, 27136]	[-10543, 27136]	[-10886, 27136]	[-10208, 27136]	[-13362, 27136]	[-11544, 27136]
GDP per capita * Autocracy	1011.29	1104.897	1001.646	1066.729	1066.91	1033.573	942.189	1016.37	1016.547	1059.206	1076.754	1047.077	1036.483	1053.094	1067.348	1053.481	1043.142	1032.045	1018.926	1085.889	1054.69
	[0, 14901]	[-6434, 14901]	[-5593, 14901]	[-6755, 14901]	[-6811, 14901]	[-7331, 14901]	[-5916, 14901]	[-7501, 14901]	[-6617, 14901]	[-6844, 14901]	[-6590, 14901]	[-7435, 14901]	[-5870, 14901]	[-7224, 14901]	[-6604, 14901]	[-7274, 14901]	[-6512, 14901]	[-6899, 14901]	[-6847, 14901]	[-7614, 14901]	[-6717, 14901]

Note: Mean values marked in bold deviate from the observed mean by more than 25 per cent. The first number in the square brackets is the minimum value, while the second number is the maximum value, i.e. [min value,max value].

Appendix F (continued)

Simulations quarterly data set

		Simulations																			
	Observed value	m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10	m=11	m=12	m=13	m=14	m=15	m=16	m=17	m=18	m=19	m=20
J-curve political	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.006	0.005	0.005	0.005	0.005
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
J-curve GDP/capita	0.012	0.012	0.012	0.012	0.012	0.012	0.013	0.012	0.013	0.012	0.012	0.013	0.012	0.013	0.012	0.012	0.012	0.011	0.012	0.012	0.012
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Polity	0.633	0.59	0.632	0.545	0.621	0.575	0.626	0.57	0.647	**0.414**	0.7	0.738	0.574	0.658	0.653	0.725	0.569	0.681	**0.814**	0.64	0.58
	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]
Gini	43.287	43.716	43.287	43.804	44.126	44.195	42.63	43.541	42.814	43.103	42.835	44.364	44.183	44.87	43.978	44.153	44.232	43.015	44.251	43.868	43.534
	[30,67]	[18, 130]	[18, 125]	[20, 137]	[12, 167]	[14, 163]	[15, 156]	[18, 124]	[14, 154]	[13, 141]	[17, 124]	[20, 146]	[14, 175]	[21, 179]	[11, 150]	[17, 150]	[18, 139]	[11, 114]	[16, 157]	[16, 127]	[16, 170]
ICT growth	0.16	**0.094**	0.121	**0.097**	**0.115**	**0.1**	0.142	**0.103**	**0.092**	0.122	**0.106**	**0.118**	0.142	**0.102**	**0.102**	**0.094**	**0.104**	**0.091**	**0.091**	**0.089**	**0.103**
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
International trade (% of GDP)	74.639	75.127	74.914	75.293	74.092	73.63	74.531	74.955	74.734	75.373	74.733	74.153	74.266	75.572	73.854	74.879	74.213	75.563	75.157	74.142	74.672
	[18, 275]	[-53, 275]	[-37, 275]	[-52, 275]	[-40, 275]	[-45, 275]	[-36, 275]	[-50, 275]	[-58, 275]	[-46, 275]	[-32, 275]	[-36, 275]	[-42, 275]	[-27, 275]	[-53, 275]	[-52, 275]	[-37, 275]	[-60, 275]	[-52, 275]	[-69, 275]	[-59, 275]
GDP per capita	1932.995	1896.659	1793.674	1956.431	1860.065	1959.611	1852.426	1877.457	1763.84	1927.229	1900.817	1819.607	1848.581	1834.095	1802.523	1923.262	1919.42	1817.238	1815.243	1866.881	1779.165
	[102, 27136]	[-9519, 27136]	[-9134, 27136]	[-13872, 27136]	[-11431, 27136]	[-9739, 27136]	[-10228, 27136]	[-10971, 27136]	[-10681, 27136]	[-11213, 27136]	[-9754, 27136]	[-10130, 27136]	[-12764, 27136]	[-12511, 27136]	[-11752, 27136]	[-13510, 27136]	[-9641, 27136]	[-11044, 27136]	[-10095, 27136]	[-8967, 27136]	[-11195, 27136]
GDP per capita * Autocracy	1011.29	995.803	1052.315	1029.237	1041.209	1005.966	1044.833	992.744	1077.909	977.253	993.867	986.967	1030.369	921.966	1054.951	1057.699	1004.444	1009.016	999.475	1014.236	971.27
	[0, 14901]	[-6050, 14901]	[-4540, 14901]	[-5565, 14901]	[-4954, 14901]	[-5327, 14901]	[-7272, 14901]	[-6777, 14901]	[-5419, 14901]	[-5811, 14901]	[-6126, 14901]	[-5819, 14901]	[-6274, 14901]	[-5539, 14901]	[-5661, 14901]	[-7416, 14901]	[-5779, 14901]	[-5066, 14901]	[-5475, 14901]	[-6061, 14901]	[-5934, 14901]

Note: Mean values marked in bold deviate from the observed mean by more than 25 per cent. The first number in the square brackets is the minimum value, while the second number is the maximum value, i.e. [min value,max value].

Appendix F (continued)

Simulations yearly data set

	Observed value	Simulations m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10	m=11	m=12	m=13	m=14	m=15	m=16	m=17	m=18	m=19	m=20
J-curve political	0.005	0.005	0.005	0.005	0.005	0.005	**0.008**	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	**0.009**	0.005	0.005	0.005	0.005	0.005
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
J-curve GDP/capita	0.012	0.011	0.011	0.013	0.014	0.015	0.011	0.011	0.014	0.015	0.014	0.015	0.014	0.011	0.011	0.014	0.011	0.011	0.013	0.011	0.014
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
Polity	0.633	0.636	0.608	0.644	0.633	0.704	0.644	0.638	0.713	0.639	0.643	0.656	0.680	0.625	0.659	0.660	0.623	0.690	0.640	0.700	0.694
	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]	[-9,10]
Gini	43.287	44.880	43.702	44.960	43.490	43.716	43.717	44.588	45.394	44.177	45.657	44.694	44.994	43.669	44.814	42.571	45.092	44.531	44.211	44.877	44.915
	[30,67]	[8,326]	[6,314]	[4,327]	[13, 257]	[8,285]	[14, 143]	[15, 242]	[11, 316]	[20, 299]	[23, 259]	[21, 205]	[21, 230]	[17, 247]	[16, 249]	[15, 238]	[14, 252]	[4,306]	[5,214]	[20, 281]	[20, 286]
ICT growth	0.16	0.174	0.185	0.146	**0.068**	**0.229**	**0.085**	0.131	0.158	**0.076**	**0.098**	0.158	**0.108**	0.146	0.129	**0.111**	0.123	**0.079**	**0.093**	**0.083**	**0.054**
	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]	[0,1]
International trade (% of GDP)	74.639	75.125	74.641	74.351	75.058	75.228	74.472	75.061	75.083	74.451	74.458	74.415	74.729	74.692	75.09	74.786	74.703	74.738	74.816	74.697	74.748
	[18, 275]	[-8,275]	[-5,275]	[-2,275]	[-6,275]	[1,275]	[-8,275]	[-9,275]	[1,275]	[0,275]	[-13, 275]	[-69, 275]	[-2,275]	[-26, 275]	[8,275]	[10, 275]	[-9,275]	[6,275]	[-23, 275]	[1,275]	[-3,275]
GDP per capita	1932.995	1886.51	1886.669	1895.545	1853.038	1881.627	1900.742	1818.371	1906.944	1842.438	1900.103	1894.381	1868.363	1882.794	1866.664	1861.126	1946.131	1887.698	1871.87	1903.959	1877.685
	[102, 27136]	[-9008, 27136]	[-7159, 27136]	[-8606, 27136]	[-7799, 27136]	[-7554, 27136]	[-7108, 27136]	[-7174, 27136]	[-7131, 27136]	[-7445, 27136]	[-7510, 27136]	[-6689, 27136]	[-9409, 27136]	[-8294, 27136]	[-10497, 27136]	[-7709, 27136]	[-9770, 27136]	[-5475, 27136]	[-4912, 27136]	[-6341, 27136]	[-9452, 27136]
GDP per capita * Autocracy	1011.29	981.725	1019.359	1019.144	1023.382	1014.428	1006.634	1044.479	1014.697	971.852	1012.827	1004.582	1025.577	1049.47	1047.469	1034.771	1028.074	1038.855	1016.847	992.723	1037.886
	[0, 14901]	[-3591, 14901]	[-3981, 14901]	[-1932, 14901]	[-5386, 14901]	[-3875, 14901]	[-4861, 14901]	[-2778, 14901]	[-2701, 14901]	[-4546, 14901]	[-4298, 14901]	[-3139, 14901]	[-4453, 14901]	[-3525, 14901]	[-2141, 14901]	[-1677, 14901]	[-4453, 14901]	[-2476, 14901]	[-3569, 14901]	[-2153, 14901]	[-4132, 14901]

Note: Mean values marked in bold deviate from the observed mean by more than 25 per cent. The first number in the square brackets is the minimum value, while the second number is the maximum value, i.e. [min value,max value].

Appendix G

Full regression output for SAR and SEM using the fixed effect estimator

	SAR						SEM					
	Inverse distance			Contiguity			Inverse distance			Contiguity		
	Monthly	Quarterly	Yearly	Monthly	Quarterly	Yearly	Monthly	Quarterly	Yearly	Monthly	Quarterly	Yearly
Rho	-0.025	-0.027	0.394	0.021	0.031	0.392						
	(0.049)	(0.069)	(0.608)	(0.018)	(0.022)	(0.606)						
Lambda							-0.101	-0.134	-0.034	0.017	0.015	0.013
							(0.089)	(0.101)	(0.216)	(0.021)	(0.031)	(0.072)
J-curve political	0.175	0.769	3.439	0.176	0.781	3.511	0.284	0.768	5.605	0.269	0.686	5.301
	(0.238)	(1.149)	(13.153)	(0.237)	(1.155)	(13.125)	(0.411)	(1.705)	(18.414)	(0.405)	(1.691)	(18.313)
J-curve GDP/capita	0.277	0.575	3.209	0.265	0.519	3.029	0.627	1.511	3.146	0.584	1.371	3.121
	(0.269)	(0.891)	(9.376)	(0.272)	(0.905)	(9.415)	(0.484)	(1.533)	(9.167)	(0.483)	(1.534)	(9.137)
Polity	**0.026****	0.051	0.389	**0.026****	0.049	0.386	**0.038****	**0.077***	0.634	**0.038****	0.076	0.637
	(0.013)	(0.042)	(0.637)	(0.012)	(0.042)	(0.635)	(0.017)	(0.046)	(0.717)	(0.017)	(0.046)	(0.714)
Lagged dependent	**0.561*****	**0.577*****	0.201	**0.561*****	**0.578*****	0.199						
	(0.079)	(0.122)	(0.149)	(0.081)	(0.123)	(0.149)						
Gini	**0.101***	**0.451*****	**2.809*****	**0.099***	**0.451*****	**2.808*****	**0.144***	**0.629****	**2.819*****	**0.144***	**0.631****	**2.817*****
	(0.055)	(0.159)	(0.831)	(0.055)	(0.159)	(0.829)	(0.086)	(0.262)	(0.756)	(0.086)	(0.263)	(0.755)
ICT growth	**0.842****	2.328	5.921	**0.842****	2.329	5.934	**1.341****	3.315	6.372	**1.345****	3.337	6.364
	(0.394)	(1.481)	(6.409)	(0.395)	(1.479)	(6.414)	(0.676)	(2.029)	(6.515)	(0.678)	(2.041)	(6.516)
International trade (% of GDP)	0.001	-0.001	0.005	0.001	-0.001	0.005	0.001	-0.001	0.007	0.001	-0.001	0.007
	(0.002)	(0.005)	(0.061)	(0.002)	(0.005)	(0.061)	(0.003)	(0.008)	(0.058)	(0.003)	(0.008)	(0.058)
Interstate war	**0.288***	1.127	0.372	**0.286***	1.119	0.407	**0.598***	1.986	0.474	**0.577***	1.915	0.308
	(0.161)	(0.958)	(8.866)	(0.157)	(0.943)	(8.846)	(0.344)	(1.546)	(8.551)	(0.328)	(1.514)	(8.493)
GDP per capita	**-0.001****	**-0.001***	0.001	**-0.001****	**-0.001***	0.001	**-0.001***	-0.001	0.001	**-0.001***	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP per capita * Autocracy	0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)

Note: *, ** and *** denote significance at the 10, 5 and 1 per cent level, respectively. Robust standard errors are presented in parenthesis. SAR is performed with a lagged dependent variable of one period, while SEM, for reasons of tractability, is performed without a lagged dependent variable. Monthly and quarterly regressions are performed with year dummies, while yearly regressions include time dummies for two-year periods.