LA-UR- 08-5107

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Intended for: Journal of Artificial Societies and Social Simulation (JASSS)

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Understanding Islamist Political Violence through Computational Social Simulation

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(Dated: July 23, 2008)

Understanding the process that enables political violence is of great value in reducing the future demand for and support of violent opposition groups. Methods are needed that allow alternative scenarios and counterfactuals to be scientifically researched. Computational social simulation shows promise in developing "computer experiments" that would be unfeasible or unethical in the real world. Additionally, the process of modeling and simulation reveals and challenges assumptions that may not be noted in theories, exposes areas where data is not available, and provides a rigorous, repeatable, and transparent framework for analyzing the complex dynamics of political violence. This paper demonstrates the computational modeling process using two simulation techniques: system dynamics and agent-based modeling. The benefits and drawbacks of both techniques are discussed. In developing these social simulations, we discovered that the social science concepts and theories needed to accurately simulate the associated psychological and social phenomena were lacking.

INTRODUCTION

Generally speaking, computer simulation attempts to represent the dynamics of a complex system based on the underlying models of its constituent components. A model takes inputs and provides output as "answers". Simulations are used to study the *dynamics* of an overall system by running different "what-if" computer experiments based on different initial conditions and different underlying component models. A key assumption is that if the component models of the simulation (the "micro-models") are well understood and valid, then the simulation can be assumed valid. When the component micro-models are invalid, then old adage "garbage in, garbage out" applies to the simulation. The difficulty in finding valid micro-models presents one of the largest challenges for computational social simulation.

Computational social simulation aims to represent the dynamics of a given social system on a computer. The practicing computational social scientist quickly discovers the dearth of empirically valid social science concepts, models, and theories when compared with the physical sciences. As Herbert Simon famously stated, "the soft sciences are the harder sciences". The physical sciences are blessed with well understood, commonly accepted, and validated models of physical phenomena. The lack of such models makes it more difficult to construct meaningful social simulations.

To illustrate the relative challenges of social simulation consider two hypothetical scenarios: (1) a simulation of a physical system and (2) a simulation of a social system. In the physical system, engineers may construct a simulation of rocket trajectories to evaluate different rocket designs. The validity of this rocket simulation can be assessed by reviewing its underlying models of gravity, thrust, air resistance, etc. The engineers share a *common* set of fundamental rules and laws to which they can refer. They can also run experiments to characterize their rocket components (*i.e.* wind tunnel tests or engine burn tests).

In a social system, modelers may construct a simulation of three groups competing for a limited resource (*e.g.* a parcel of land). The list of social micro-models needed for this simulation is rather mind-boggling. This list includes a model for how agents become members of a group, a model of how different agents value the land parcel, a model for how groups might cooperate or form coalitions, a model for how trust is established inside and outside of groups, a model for decision-making processes inside a given group, etc. Unlike the physical sciences, there is no common agreement across the social science community as to which theory serves as the correct model for each of these phenomena, nor are there common terms of reference, for *any* of these phenomena, even in this rather simple social system.

Because the social sciences currently lack the brevity, consistency, and empirical validation found in physical science models, the question becomes what good is a computer simulation of a social system if the underlying social science micro-models are questionable?

Computer simulation provides a rigorous framework for running computer experiments on the system of interest. These experiments are easily controlled, replayed, adjusted, and monitored. Whereas a physical simulation uses valid micro-models to predict overall system (macro) effects, the computational social simulation can instead be thought of as a validation framework for adjudicating different social science concepts and models. Encoding a hypothesized social science model and its associated assumptions into a computer simulation allows one to observe how the hypothesized model behaves under different conditions and how the model behaves when its stated assumptions are relaxed. This usage of social simulation can be thought of as a macro-level test of posited micro-level models. An alternative use-case of computational social simulation is to develop macro-level theories based on very simplistic and plausible micro-level rules and heuristics. This "bottoms-up" generative approach to social science aims to understand macro-behavior based on simplistic micro-level rules [1].

Until the social sciences develop well-defined, commonly accepted, and valid models of the required social science phenomena needed to represent a social system on the computer, the use of social simulations as a general predictive tool is questionable, and limited to very specific contexts at best. Certain exceptions do exist though. Specifically, if the modelers can directly interview the persons being represented in the social simulation to elicit their motivations, influences, objectives, information resources, decision-rules, heuristics, attitudes, and behavioral repertoires, then in theory these agent-specific traits can be encoded into a computer simulation.

Computational Social Simulation Approaches

It is the job of the computational social scientist to translate qualitative theory descriptions into relationships that can be quantified using data to calibrate and validate the models. The challenge is to best represent "soft concepts" and narratives from the social sciences in forms that can be integrated into a computer simulation—i.e., mathematical relations and algorithms. Some theories are best described using mathematical relationships (e.g., utility functions [2]) whereas other theories and concepts are more easily represented by algorithmic structures (e.g., normative behavior modeled as if-then rules in computer code [3]). The system dynamics approach to social simulation lends itself to mathematical functions, specifically differential and algebraic equations. The agent-based approach to social simulation lends itself to the algorithmic representation of social-behavioral concepts.

The traditional approach to developing social science models is equation-based. Models are based on posited mathematical equations whose parameters are estimated via regression methods against data (often from surveys). If the phenomena being modeled can be accurately represented via an equation, then this approach makes perfect sense. However, models can be forced into mathematical relations that are not valid, thereby introducing model uncertainty. Model uncertainty is often ignored, whereas heroic efforts are spent trying to reduce parameter uncertainty by "just getting better data" to fit the wrong model [4]. Equation-based models have the appearance of being "more scientific" than, for example, narrative-based models; and some cases equation-based models from physics are assumed to be valid representations of social phenomena (*e.g.* spin-glass models in political science [5] [6], statistical mechanics [7]). Equation-based models are expressed in the universal language of mathematics to communicate how factors relate to each other and change over time. Mathematicians, engineers, and physicists are comfortable with equations, whereas they can be a foreign language of unfamiliar symbols to social scientists and end-users. Equations can live a life of their own, with the focus on the form of the equations and associated variants and with the question of whether or not their underlying premises are valid models of the human or social behavior they represent never asked. For example, preference curves are used to represent the concept of utility in economics.

One way to avoid the shock and awe of explaining equation-based social science models with explicit differential equations and calculus is to use a graphical simulation framework known as "systems dynamics" (SD). System dynamics is a simulation technique to models based on the concepts of stocks, flows, rates, and delays [8]. Based in control theory, system dynamics modeling requires analysis of the feedback loops that drive the system. These simulations allow one to understand multiple relationships between variables in a user-friendly, communication friendly, and transparent manner. However, the fundamental building blocks of SD models are equations that define the stocks, flows, rates, and delays. SD simulations are compatible with problems in the supply chain, macro-economic, and population growth domains; however, they can be used as preliminary investigative tools in other domains (*e.g.* social sciences). When using SD to model the social sciences, caution is advised—the modeler may be tempted to force their models to fit the stock-flow framework, rather than use the most appropriate representations for the context being modeled.

Due to their graphical representation and transparency, SD simulation techniques are good for revealing assumptions and providing an accessible interface to stakeholders [9]. When used in the social sciences, SD models require the quantification of relationships. In modeling physical systems, such as supply chains, this quantification is fairly straightforward. However, in modeling social systems, this quantification can be challenging and can expose areas where fundamental social science concepts are not well understood, as in the definition of terms (*e.g.* social identity). Furthermore, SD simulations are ideal to aid in the understanding of a system through time. Time is handled explicitly in system dynamics. Both the units and the time step are specified for the model. With this specification, ideally the model should be able to replicate data for the same time. In addition, assumptions are documented within SD software. Often in models, the place where data ends and expert opinion begins is unclear. System dynamics modelers have the ability to make this explicit. Critics of system dynamics often cite the use of constants, forcing of stock-flow relationships, and the unrealistic immediacy of effects in the simulations. However, system dynamics software is sophisticated enough to allow the specification of a distribution instead of a constant and time delays so that effects are not felt immediately. It is up to the modeler to incorporate this realism.

Computational social science can also be implemented *without mathematical equations* through algorithms. This is one of the major benefits to agent-based simulation [3]. Computer algorithms, especially when they can be diversified across a population of agents in an object-oriented programming framework (*e.g.* Java, C++) , provide a very *practical* representation of psychological, behavioral, and social phenomena. Instead of basing the model on sets of equations, the model can be based on sets of algorithm modules. For example:

```
IF agent has same ethnicity as majority of
previously arrested agents,
...AND IF agent has a resource level greater than
its neighboring agents,
...AND IF agent is unemployed,
...THEN agent sends message to ''Agent Z'',
ELSE,....
```

Algorithmic building blocks like these allow for straightforward representation of agent memory, social network dynamics, learning, imitation, and heuristic decision making, which are very important aspects of social systems. Additionally, not all agents are required to follow the same algorithms, and agents can switch or modify their rule sets based on exogenous and endogenous drivers.

The Evolution of the Simulation Problem Statement

In this paper, we share our experiences and findings in developing computer simulations for global security stakeholders interested in a gaining a better understanding of the causal dynamics that lead to political violence. Our original task was to develop a simulation that would help anticipate terrorist attacks. The assumptions going into this simulation project were that (1) social science concepts and theories existed for most of the required phenomena to be included in the simulation, (2) that ground truth demographic, economic, cultural, and political data could be collected at the level of resolution needed for the simulation, and (3) that we would be able to develop a *general* simulation that was not constrained to a specific context.

Often in computational social simulation studies, there is an over-emphasis on the results of the simulation. Certainly, a principal purpose of simulation is to gather results; however, much of the insight gained from simulation occurs during the construction of the model. The process of simulating a system is one of insight generation. The first step of the process is to translate qualitative theories into a quantitative model. Through the translation process, assumptions are noted, areas where data is lacking are exposed, and equations are formulated to formally relate entities.

The purpose of this paper is to highlight the evolution of the problem statement through insight that resulted from building simulations. The insight includes not just the results of the simulations but also the information learned throughout the model building process. It is our contention that both types of insight are vital in the struggle to understand violent political opposition organizations.

In this paper, we first discuss the simulation resulting from the original tasking to simulate terrorism in a general context based on relative deprivation theory. Next, we discuss simulations (both system dynamics and agent-based) with a specific context: Islamist political violence in authoritarian regimes (*e.g.* Egypt and Algeria). Finally, we discuss a simulation that maintains the context of Islamist political violence and focuses on one social science phenomenon: attitude dynamics. We have learned throughout the course of these simulations that highly specified simulations produce more interesting results than general simulations.

SIMULATING RELATIVE DEPRIVATION

For our original simulation tasking, we were encouraged by our sponsor to leverage what were at the time well-respected social science theories on social movements and revolutions. Specifically, we encoded the theory of relative deprivation [10] and collective action [11] into an agent-based simulation. Relative deprivation describes the disaffection that people feel when they discover that their status is much less than the status of their peers. Relative deprivation has been theorized as a potential cause of social movements which can lead to political violence, terrorism, crime, and civil wars. The social movements surface when members of a given social identity group feed deprived of what they perceive as their fair share. Relative deprivation feelings can occur at the individual level, when a person feels deprived relative to other members of their own group. This situation is an example of "egoistic" relative deprivation. When members of a given social identity group perceive their group to be in an unjustified social status position relative to another social identity group, the relative deprivation is termed "fraternal" relative deprivation. Fraternal relative deprivation can occur between ethnic, religious, tribal, or other social identities and is the form of relative deprivation associated with the build up of social movements[12]. These forms of relative deprivation are based up on an agent, or group, *comparing* itself to others.

Another form of relative deprivation that has been hypothesized as a causal factor for social unrest is based on comparing the current status, to the expected status. For example an individual may feel disappointed that their current level of income has taken a sharp downturn relative to what they anticipated it to be. This theory, known as the "J-Curve hypothesis"(see Figure 1) was originally developed by J. Davies [13]. This form of relative deprivation is also termed "unfulfilled rising expectations"[14].

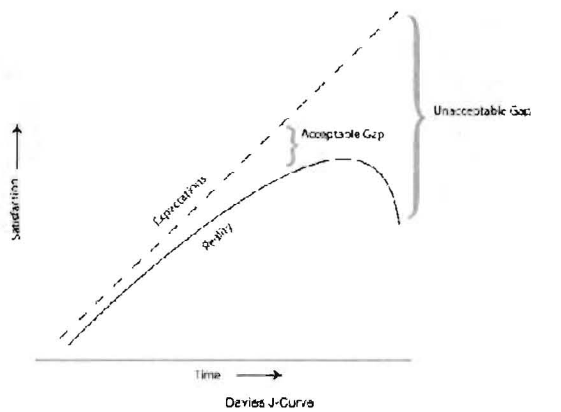

FIG. 1: The J-Curve of Davies showing how sharp downward changes in status or situation relative to the expected status increases frustration leading to social and political unrest.

Simulation Description

For our simulation model we focus only on fraternal relative deprivation and the temporal relative deprivation, the "J-Curve" hypothesis. In order to model relative deprivation we needed to represent comparisons over time between different identity groups. The simulation approach that best fit this requirement for capturing diversity in the population is agent-based simulation. We modeled agents to each have a scalar social welfare value that could change over time. The social welfare is an abstract representation of wealth, income, or status.

Individuals require certain resources for survival, such as food, water, and shelter. In addition to these vital resources, other forms of human capital such as income, health care, and education also contribute to individual welfare. Many different metrics have been developed to measure human welfare [15], [16]. There is no concensus as to which is the best of these metrics to measure human welfare. Some of these metrics focus on income (*e.g.* GDP per capita), whereas other metrics are derived from non-monetary measures (*e.g.* composite quality of life indices). Whatever metrics are chosen to assess the welfare of a population they should be representative and relevant to the persons under study - for example, income metrics may be irrelevant in the most primitive socieities.

Most real world indices of welfare are reported as single number statistics for ease of communication and comparison's sake. These statistical indices often do not convey the actual underlying distribution of welfare—making it difficult to measure welfare inequality across the population.

Since the welfare of an individual is affected by many different factors a number of composite indices have been designed as "better" metrics. For example, the Physical Quality of Life Index (PQLI) linearly combines three *population-based* statistics: life expectancy, infant mortality, and literacy rate into an equally weighted composite index. Another example of a population-based metric is the Human Development Index (HDI), which combines measures of life expectancy, education, and income into a single metric based on average measures. (The procedure for calculating the HDI is given in the Appendix).

For the purposes of our model we need a *heterogenous* metric for the *individual* welfare of each agent. This metric can be simply thought of as a *time varying scalar* quantity, $w_i(t)$, used to measure the welfare at time t of an individual agent indexed by i. The challenge lies in using a metric that is *comparable to real world measures* of welfare. If the actual *distributions* of the component quantities used to calculate composite welfare indices (*e.g.* HDI or PQLI) are available, then, in principle, each agent could be initialized via statistical sampling from these distributions for quantities such as years of education, real income, and expected lifetime. Ideally, the real world correlations (*i.e.* correlation between education and income), between these quantities would also be available and included in generating a population of agents for study.

Since the focus of our research is not in finding a single best index to represent human welfare, we proceed with a simplistic model for the welfare measure for an individual agent. We posit that the welfare of an individual is a multiplicative function of access to vital resources needed for life, such as food and water, multiplied by income and education levels. We represent the individual welfare, $w(t)_i$, of an agent i as,

$$w_i(t) \approx \frac{1}{3} \times v_i(t) \left[1 + c_{i,inc} i_i(t) + c_{i,edu} e_i(t)\right], \qquad (1)$$

where the vital resources necessary for survival is modeled as,

$$v_i(t) \equiv \max\left[0, \frac{\left(V_i(t) - V_i^{MIN}\right)}{\left(V^{MAX} - V_i^{MIN}\right)}\right], \qquad (2)$$

Here $V_i(t)$ is the level of "vital resources" that agent i has access to at time t. A real-world proxy for this variable might be daily caloric input [17]. The minimum level of vital resources for an agent i is V_i^{MIN} , which can be considered the threshold needed for survival and is heterogenous across the population of agents. V^{MAX} is the maximum amount of vital resources that is held by one individual in the population under study. Note that the vital resources component of individual welfare is normalized so that $v_i(t) \in [0, 1]$. Similarly, we estimate the contribution of income to welfare as,

$$i_i(t) \equiv \max\left[0, \frac{\left(I_i(t) - I_i^{MIN}\right)}{\left(I^{MAX} - I_i^{MIN}\right)}\right], \tag{3}$$

with $I_i(t)$ representing the real income (in purchasing power parity) of agent i at time t. The agent's income $I_i(t)$ is compared with a minimum income threshold level I_i^{MIN}. The maxium income of the wealthiest individual in the population is I^{MAX}. The educational component to individual welfare is similarly estimated as,

$$e_i(t) \equiv \max\left[0, \frac{\left(E_i(t) - E_i^{MIN}\right)}{\left(E^{MAX} - E_i^{MIN}\right)}\right], \tag{4}$$

where $E_i(t)$ is the educational capital of an agent at time t, and $E_i^{MIN}$is the minimum educational capital (for example, years of school) that is expected in the local community of the agent. The contributions to welfare from income and education are linearily combined in the second term of Eq.(1). The amount that a particular agent values income over education in its social welfare is defined by the two weighting factors $c_{i,inc}$ and $c_{i,edu}$ in Eq.(1). Each of the weighting factors is chosen to be in the range $[0,1]$. The terms V^{MAX}, I^{MAX}, and E^{MAX} refer to the maximum values found in the entire population for each respective quantity. Note that the welfare function, Eq.(1), is normalized so that it carries no units of measure.

Examining the behavior of Eq.(1) in a number of different cases is useful. First, the welfare function is bounded inside the interval $w_i(t) \in [0,1]$. The welfare function is equal to zero only when the vital resources fall below the threshold level for minimum required vital resources. This limiting behavior emphasizes that vital resources are a fundamental requirement of life regardless of income and education levels. This welfare function is constructed much differently than the HDI index — mainly due to the leading multiplicative term. The HDI index combines the three components of health, education, and income in a linear relationship. An interesting special case of the HDI measure is that a person with minimal life expectancy can still have a relatively high HDI value if their income and education levels are high enough. In reality, however, this special case is probably rare (with the possible exception of individuals with life shortening diseases such as HIV) due the actual correlations between the terms of the HDI index.

To represent relative deprivation agents compare their own social welfare to those of other agents. They compare their social welfare locally, nationally and globally. In different cultures around the world the visibility of social welfare varies, however, as globalization and global media access increase it is easier for a person in a far off developing country to "see" the social welfare from a far off location—for example watching television shows of Hollywood life in a North African farming village. Mathematically we estimate the perceived hardship for agent i, psh_i, from this social welfare comparison as,

$$\begin{aligned} psh_i(t) &\equiv \nu_{i,r}\left[1 - r_{i,w}(t)\right] \\ &+ \nu_{1,n} f_{press}\left[1 - n_{i,w}(t)\right] \\ &+ \nu_{i,w} \sum_{e=1}^{N_{groups}} f_{cp}^{e \to i}\left(HDI_e - HDI_i\right). \end{aligned} \tag{5}$$

Here $r_{i,w}$ is the rank of social welfare that agent i has in its local community. The "visibility" (or awareness) that this agent has of the social welfare of other agents in this community is denoted by the weight $\nu_{1,r} \in [0,1]$. Similarly, agents have varying degrees of "national-visibility" of the social welfare of agents in their respective nations denoted by $\nu_{1,n} f_{press} \in [0,1]$. We have weighted the national-visibility of social welfare by the freedom of press index, f_{press}, to capture the effects of varying levels of media filtering of this visibility[18]. An agent's national rank of social welfare is given by $n_{i,w}$. The contribution to relative deprivation from an agent comparing its social welfare to others around the world is based on their host countries human develop index, HDI_i, compared to that of other countries, weighted by a world-visibility term of $\nu_{i,w}$. Cultural penetration of country e into the host country of agent i is represented by the weighting factor $f_{cp}^{i \to e}$ to capture diversity in cross-cultural influences between nation state pairings.

During the development of the simulation we expending too many resources on finding real-world data for many of the socioeconomic measures in Eqns.(1-5) . Some of these parameters were readily available, such as the Human Development Index (HDI), the Worldwide Press Freedom Index (f_{press}), the income distributions, and the education distributions[21]. We did not find real-world data for the cultural penetration factor, $f_{cp}^{e \to i}$. We also did not have real-world data for estimating the social welfare visibility weights $\nu_{1,r}$, $\nu_{1,n}$, and $\nu_{1,w}$. The weights we did not have real data for were simulated by sampling from a normal distribution when creating the agent populations. We notionally simulated sample populations in Algeria, Egypt, and Iraq based on the readily accessible input data.

The dynamics of the agents included each agent monitoring the social welfare of randomly sampled other agents at the local district level and the national level. Each time they sampled the welfare of other agents they would update their respective values for Eq.(5), which also included re-ranking their respective social welfare ranks. Agent visibility weights $\nu_{1,X}$ were created at the initialization of a simulation run by sampling input (normal) distributions and remained static for the course of the simulation run.

Exogenous economic shocks were introduced into the simulation that affected agents income distributions and user defined intervals of time. These shocks were modeled as a stochastic process that reduced each agents income distribution by a constant percentage at each shock interval. This would affect the welfare ranking of the each agent over time.

We modeled the temporal effects of relative deprivation, the J-Curve hypothesis[13], by having each agent track its current level of income relative to its previous values of income to estimate a missed expectations of income metric, $mE_i(\tau)$,

$$mE_i(\tau) = max\left[0, \int_0^{\tau} \left(w_{i,expected}(t) - w_{i,current}(t)\right) dt\right] \quad (6)$$

The relative deprivation agent-based simulation (officially called the Threat Anticipation Program Agent Simulation, or "TAPAS") was developed using the Java RePAST agent-based framework[22]. A screen shot of the TAPAS software is shown in Fig.(2).

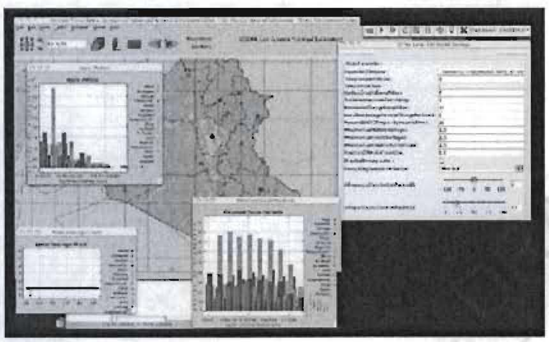

FIG. 2: A screen shot of the Threat Anticipation Program Agent Simulation (TAPAS) interface showing a typical simulation output of perceived social hardship from relative deprivation of social economic factors. Agent populations can be generated in different sub-national administrative districts. In theory ground truth socioeconomic data distributions could be used at the administrative district level, however, for our initial prototype testing we used national level distributions.

Simulation Results

The relative deprivation agent-simulation, TAPAS, was able to generate populations of agents from input socioeconomic data sources. These agents monitored their relative social welfare compared to other agents and how it changed individually over time. We used empirical data for Algeria, Egypt, and Iraq for the socioeconomic data, however, we did not have data for the visibility parameters. These were left as variables for the end user to adjust. Based on the input data we did not see any huge relative deprivation signatures. This may have been due to the resolution of our data sets and the fact that we were modeling different administrative districts (where actual levels of relative deprivation may have been high) with socioeconomic data aggregated up to the national level? A sample output distribution of perceived social hardship from the TAPAS simulation is shown in Fig.(3).

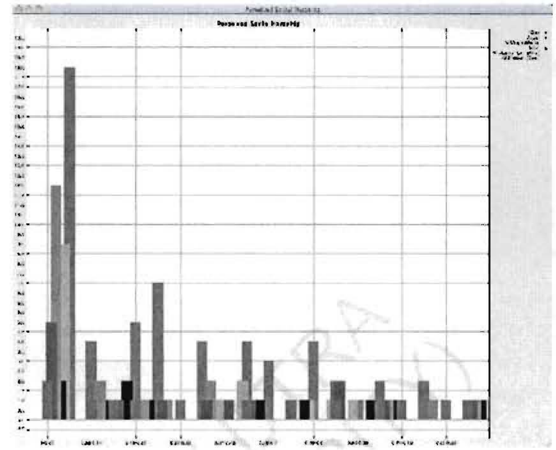

FIG. 3:

At this point in our research we could have either tried to find better data, resolved to the district levels in the nation states modeled, or reinvestigate our overall direction. Questions arose as to whether or not the agent-based simulation was over-specificed relative to the available data it required.

Additionally, shortly after completing this phase of the simulation, Mohammed Hafez in "Why Muslims Rebel" [19] presented both a refutation of relative deprivation as the prime motivator of Islamist political violence and an alternative theory. The Hafez theory is a departure from the popular relative deprivation theory of political violence. Hafez contends that relative deprivation is not an empirically sound explanation of Islamist political violence because some Muslim countries have experienced similar socio-economic changes without rebellion.

Hafez displays the economic indicators of five predominantly Muslim countries to demonstrate that purely economic arguments of political violence, such as relative deprivation, do not account for Islamist rebellion. In Figure 4, the socio-economic indicators of Algeria, Egypt, Jordan, Morocco, and Tunisia are relatively similar; however, Egypt and Algeria experienced many more incidents of political violence during this time period than the other three countries.

In Figure 5, Hafez illustrates the number of violent incidents in Egypt and Algeria over a thirty-one year time period. Note the very explosive peaks in Islamist violent incidents in both Egypt and Algeria that starts around 1990. Hafez explains the causal factors that lead up to these peaks based on political exclusion of the Islamists by the authoritarian regimes, repressive actions of the regimes, and anti-civilian violence by the Islamists in the

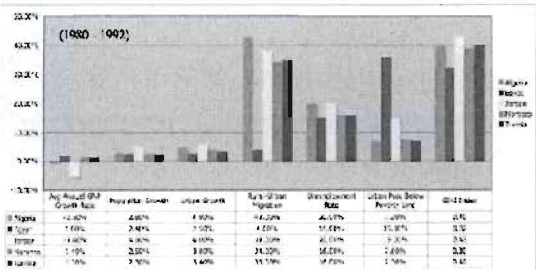

FIG. 4: Socio-economic indicators across five Muslim countries from 1980-1992. Despite similar economic situations, Egypt and Algeria experienced many more violent political incidents than in the other three countries. Figure adapted from [19].

mass rebellion phase—instead of a relative deprivation basis for rebellion.

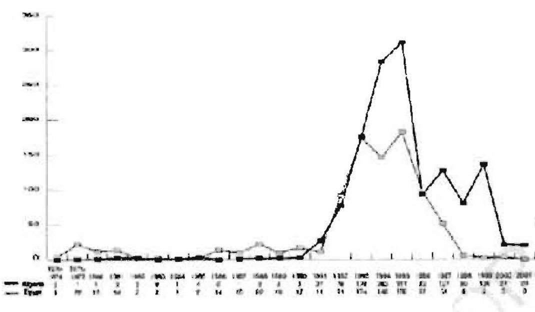

FIG. 5: The number of violent incidents versus time for Algeria (dark curve) and Egypt (light curve). Image from [19], p. 33.

The Hafez theory describes the necessary and sufficient conditions to produce radicalization, the process through which a political opposition group becomes violent. The theory contends that Islamist political organizations resort to violence under certain conditions of an authoritarian regime. Hafez [19] provides a qualitative description of this theory:

> ...Muslims rebel because of an ill-fated combination of institutional exclusion, on the one hand, and on the other, reactive and indiscriminate repression that threatens the organizational resources and personal lives of Islamists. Exclusionary and repressive political environments force Islamists to undergo a near universal process of radicalization, which has been witnessed by so many rebellious movements, including ethnonationalist, socialist, and right-wing movements (p. 21).

Based on Hafez's findings we opted to develop a social simulation of his theory. We chose to use systems dynamics to capture the general factors and dynamics of the Hafez theory. An agent-based simulation of the entire Hafez framework, especially modeled after a real-world context (e.g. Egypt) would be an over ambitious starting point.

SYSTEM DYNAMICS SIMULATION OF ISLAMIST POLITICAL VIOLENCE

While system dynamics modeling is a general framework with multiple uses, we are stressing two roles developed in the subsections below. One, developing a system dynamics model is a way to carefully review theories so as to surface underlying assumptions. Two, once the model is created and the mathematical relationships specified, the model can be run as a simulation so as to test hypotheses.

Simulation Description

The purpose of this system dynamics simulation is to gather insight into how various changes in government strategy could change the amount of violence perpetrated by Islamist political organizations. In terms of the Hafez model, we are interested in understanding the role of political exclusion, preemptive and reactive timing, and selective and indiscriminate targeting on the number of rebellions.

The challenge of systems dynamics is to translate from theory to a corresponding simulation of stocks and flows. The first simplification of the theory is to reduce the space of political opposition groups to one. This reduces the complexity involved in modeling group competition and cooperation, merging and fissuring, even though Hafez's theory describes these interactions. As it is the number of rebellions that is of interest, it is useful to determine the factors suggested by the theory that produce positive feedback for rebellions (growth) and the factors that produce negative feedback for rebellion. Hafez suggests that the number of radicals, the group's popular support, and the need to defend the group are all factors that increase rebellion. On the other hand, factors that prevent rebellion from increasing are those that restrict resources or temper or remove radicals.

From this simple causal structure, the model begins to take shape. The number of rebellions is modeled as a stock. The stock is increased with each act of violence, but there is no way to decrease the stock just as there is no way to undo a violent act. In system dynamics terms, if the goal of the government is to stop rebellions, then the rate of violence must be brought to zero. The next step is to add to the model the positive feedback factors. The number of radicals is one such factor. Hafez defines Islamist radicals as those who believe violence is necessary to achieve their aims. In the model, radicals are represented as a stock. The number of radicals contributes to the violence rate such that the more radicals there are (above a minimum threshold), the more the `violence desire`. While this mathematical relationship is indicated by Hafez, the formal relationship must be assumed by the modeler.

The second factor that increases the rate of rebellion is the group's popular support. A group can gain popular support if the government engages in indiscriminate targeting. If the government represses those only loosely affiliated with the group or not affiliated at all, the group will gain sympathy in the form of popular support. Hafez states that the mechanism that links popular support to violence is through an increase in legitimacy and identity resources. In the model, all resources, whether material, institutional, or legitimacy-based, are modeled as a single stock. Support increases depending on the number of radicals. Again, Hafez indicates this relationship, but in the absence of data, the mathematical relationship must be determined by the modeler. Resources are a constraining factor on violence. The group can only commit the number of violent acts that they have the resources to support. Another important simplification of this model is the homogenous nature of the rebellions—all rebellions require identical resources and have the same effects. In the Hafez theory, the primary motivator of radicalization, the rate that increases the number of radicals, is political exclusion.

The third factor that increases the rate of rebellion is the perception of the groups endangerment. The Hafez model contends that when the government acts too late to deflate a growing movement, there are unintended consequences. If the government represses an Islamist political organization when it already has the resources needed to be violent, then the group also has the ability to retaliate against this repression. Furthermore, the group feels that it must retaliate for its own survival—it acts in a violent manner for defense.

There are also factors that reduce the violence rate. Just as reactive timing increases violence, preemptive timing reduces violence by restricting the ability of the political organization to acquire resources. There are a number of ways to model timing in system dynamics. Delays are often modeled using conveyors that hold an amount for a specified lag time. In the present model, timing can be introduced by linking preemptive and reactive constants to different parts of the model, with reactive timing affecting the point closest to actual rebellion. The violence rate can also be slowed by changing the number of radicals. If the government is inclusive, the number of radicals fail to reach a threshold where mass movements are possible. Alternatively, the government can engage in selective targeting, whereby a portion of the radical population is removed from the movement. Finally, most simply, rebellion is constrained by past rebellions, which reduce the available resources.

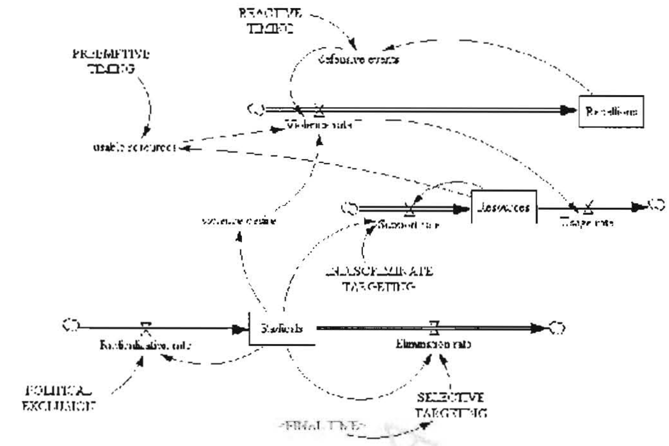

FIG. 6: The stock and flow diagram of the relationship between regime legitimacy and opposition group violence in VenSim.

Figure 6 is the completed stock and flow diagram of the system dynamics model. In describing the process to construct this model it is clear that the modeler must make many assumptions involving the mathematical expression of what has only been described in words. The availability of data removes this burden from modelers. However, often terrorism-based models are needed for situations without historical precedence of terrorist activity so that data is unavailable. Additionally, the system dynamics model is accomplished most elegantly through an abstraction from heterogeneity to homogeneity; despite the wealth of differences between radicals, between resources, and between rebellions, they are all modeled uniformly.

Simulation Results

As illustrated in Figure 6, there are five constants indicated by the all capitals lettering. These five constants are also the variables for the simulation. As stated, the purpose of the simulation is to test whether more accurate repression or less political exclusion will reduce the number of rebellions by the end of a thirty-one year time period. This time period is the length of time studied by Hafez in his analysis of Islamist political violence in Egypt and Algeria.

We can think of the combination of the five variables as representative of broad governmental strategies. For example, a lassez-faire strategy would involve total political participation and no repression of any kind. Alternatively, an extreme authoritarian and ineptly repressive government would completely exclude political participation and would repress indiscriminately and reactively.

By altering the level of political exclusion, the selective and indiscriminate targeting, and the preemptive and reactive timing, we can investigate the role of these factors in reducing rebellion.

Before discussing the results of simulating various strategies, some features of the variables should be discussed. All five variables vary from 0 to 1. Following Hafez's theory, political exclusion is considered an autonomous variable. A government can be as inclusive or exclusive toward the group as they please. The other four variables describe repression attempts of the government. There are two categories of repression: timing and targeting. Within these two categories there are apt strategies (namely preemptive timing and selective targeting) and there are inept strategies (namely reactive timing and indiscriminate targeting). Note that the strategies vary independently. For example, a government can engage totally in both preemptive and reactive timing.

To determine which governmental strategies most effectively inhibit rebellion, we examined seven strategies and their resultant number of rebellions within the same time period. Note that each stock requires an initial value. For all results the initial value of `Rebellions` was 0, of `Resources` was 10, and of `Radicals` was 100. The definition of the strategies appear in Table I results are summarized in Figure 7.

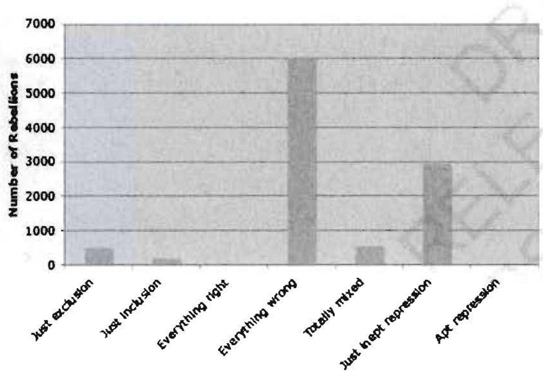

FIG. 7: The number of rebellions resulting from each government strategy.

It is clear from Figure 7, that political inclusion without any form of repression is not sufficient to stop rebellion. However, this "Just inclusion" strategy resulted in only 182 acts of rebellion whereas the "Just exclusion" strategy resulted in the 493 acts of rebellion in the same time period. From this we can conclude that repression should play an important part in a government's strategy to prevent rebellion. However, the results also conclude that the type of repression is important. Both the strategies that engaged in preemptive timing and selective targeting ("Everything right" and "Apt repression") resulted in zero acts of rebellion. This is an encouraging result for authoritarian regimes that wish to maintain their exclusionary policies. These results suggest that as long as the repression tactics are effective, political exclusion cannot produce rebellion.

The effect of political exclusion in a two-group systems dynamics simulation, with one group be moderate and one radical (willing to use violence), is shown in Fig.(8). After a sudden reduction in political participation, moderate agents move to the radical group, since their grievances increase, and they move to the only available channels for influence open to them – violent ones.

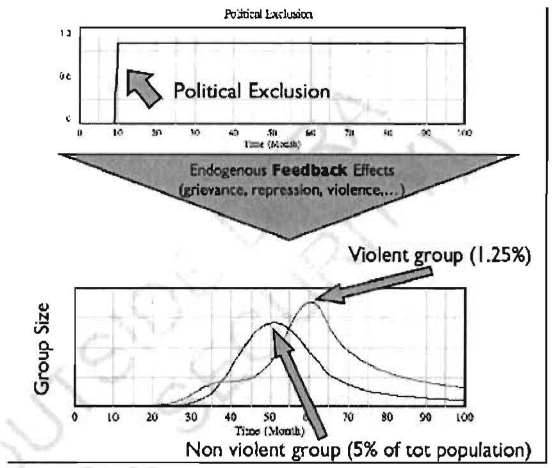

FIG. 8: After a sudden reduction in allowed political participation for all Islamist groups, moderate Islamists (blue) migrate towards the more radical Islamist group (red) over time.

The effects of targeting the violent Islamists is shown in Fig.(9). Different simulation runs represent different levels of targeting accuracy by the regime. Low targeting accuracy increases collateral effects, where non-combants are repressed (arrested, tortured, killed), increasing outrage in the general population and reducing support for the regime, and increasing recruitment and support for the opposition groups.

Every model is a work in progress and this system dynamics model is no exception. The purpose of this basic model is to test the effect of various policies through time. However, it is more likely that a government will change its policies in response to the environment. In other words, rather than maintain a continuous value throughout the whole thirty-one year time period, each of the five variables should be capable of change. The next iteration of this model will include this more realistic capability.

LESSONS LEARNED

Having a well defined context with crisp simulation goals helps to narrow the focus and reduce unnecessary

Strategy	political exclusion	selective targeting	indiscriminate targeting	preemptive timing	reactive timing
Just exclusion	1	0	0	0	0
Just inclusion	0	0	0	0	0
Everything right	0	1	0	1	0
Everything wrong	1	0	1	0	1
Totally mixed	.5	.5	.5	.5	.5
Just inept repression	0	0	1	0	1
Apt repression	.5	1	0	1	0

TABLE I: The definition of strategies by each variable in the system dynamics model.

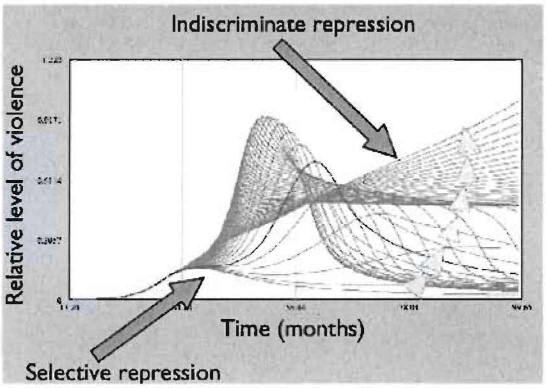

FIG. 9: The effect of targeting effectiveness (selective or indiscriminate repression) is shown here. If the regime is able to accurately target and repress the violent radicals early on in the simulation, then the overall violence level is minimized – as compared to indiscriminate repression.

complexity in the simulation. We went from simulating "terrorism" to a well defined focus on Islamist violence in authoritarian regimes. This transition helped dramatically in providing value from social simulation. When the context of the simulation problem is well defined it is also easier to interpret results and validate the models used to construct the simulation. A second reason, and the primary point of this paper, is that the micro-models that comprise a simulation are better specified for specific contexts, than for general contexts. The quality of the simulation is dependent on the quality of these underlying models.

There is huge demand for computational social science software to be applied to current global security problems. This is good for providing the needed resources for advancing this relatively new field of social science. However, any assumptions that "text-book" social science concepts and theories can be directly encoded into computer simulations and applied to these real-world problems should be seriously considered.

Computational social science methods (especially agent-based simulation) do show great promise though for actually advancing the social science theories and concepts. More and more empirically derived social science theories are being developed from experimental economics and psychology, functional magnetic resonance imaging experiments, and cross-disciplinary research of psychological, social, and behavioral phenomena. Computational social science provides a framework for further developing these new findings, vetting and comparing their implications, and applying them to specific contexts.

APPENDIX: CALCULATING THE HUMAN DEVELOPMENT INDEX

The United Nations Development Program (UNDP) constructed a composite index, the Human Development Index (HDI), in 1990 to measure the average achievements of a nation in basic human capabilitiesUNDP [20].' The HDI is a composite index based on an index of life expectancy at birth, I_H, educational attainment, I_E, and real GDP in purchasing power dollars to measure the standard of living., I_I . Each of these component indicies is calculated as follows:

The health component to HDI is calcualted as,

$$I_H = \frac{(H - H^{MIN})}{(H^{MAX} - H^{MIN})}, \tag{7}$$

where H is the life expectancy at birth in average years, $H^{MIN} = 25$ years is minimum life expectancy, and $H^{MAX} = 85$ years is the maximum life expectancy as used by the UNDP. This component index of the overall HDI index ranges from $[0, 1]$'.

The educational component to HDI is actually composed of two sub-indices: one that measures literarcy rates and another that measures school enrollments. The functional literacy index, E_1, given by,

$$E_1 = \frac{(Lit - Lit^{MIN})}{(Lit^{MAX} - Lit^{MIN})}, \tag{8}$$

where Lit is the literarcy rate, $Lit^{MIN} = 0$ and $Lit^{MAX} = 100$. Note that $E_1 \in [0, 1]$. Measures of enrollment in elementary and secondary schools are estimated by the index, E_2, given by,

$$E_2 = \frac{(Enrol - Enrol^{MIN})}{(Enrol^{MAX} - Enrol^{MIN})}, \quad (9)$$

where $Enrol$ is the combined enrollment rate in elementary and secondary school, $Enrol^{MAX} = 100$ and $Enrol^{MIN} = 0$. The range of E_2 is $E_2 \in [0, 1]$. The two sub-components of the educational component of HDI are combined into a single educational component, I_E, as

$$I_E = \frac{2}{3}E_1 + \frac{1}{3}E_2, \quad (10)$$

so that literacy is weighted more important to human development than school enrollment.

The third component of HDI relates to income. This component, I_I, is calculated as,

$$I_I = \frac{(Y - Y^{MIN})}{(Y^{MAX} - Y^{MIN})}, \quad (11)$$

where Y is the real income per capita and the maximum and minimum values are the highest and lowest per capita income actually obtained in the population of interest.

The final calculation of the composite HDI index is given by the average of the three sub-components,

$$HDI = \frac{I_H + I_E + I_I}{3}. \quad (12)$$

We thank the Defense Threat Reduction Agency, Advanced Concepts Office for initiating ground-breaking research of threat anticipation studies and allowing our team to learn more about this fundamentally important area of science and international security.

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