

A simulation of state systems

Benjamin Horvath

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Abstract

This paper uses a computer simulation to shed light on contradictory hypotheses generated from the realist school of international relations. It draws on the work of Cusack and Stoll (1990b). The simulation initializes 98 primitive states, which then ally with and fight wars against each other, governed by simulation parameters set by the researcher. Nearly 1600 simulations were ran and recorded. Parametric survival analysis is used to adjudicate between competing theories. The results are broadly consistent with Cusack and Stoll in that key variables are shown to be statistically significant, refuting ‘automatic stabilization’ theories of state systems.

Contents

1	Introduction	2
2	States and State Systems	2
3	The Simulation	6
3.1	Phase 1: Select the ‘protagonist’ state	7
3.2	Phase 2: Diplomacy	7
3.3	Phase 3: War	8
3.4	Phase 4: Power adjustment and economic growth	11
4	Results	11
4.1	State Survival	13
4.2	System Survival	17
5	Conclusions	20
6	References	21

1 Introduction

Most international relations theorists are not known outside the academia or Washington D.C., but the ones that are typically belong to the *realist* school—including Thucydides, Machiavelli, and Henry Kissinger. Despite its prominence, a specifically realist doctrine can be difficult to pin down. Not only do realist theorists often start from different assumptions, they can also generate contradictory hypotheses.

The central questions of realist discourse are:

1. How does a community of states (*state system*) maintain stability?
2. What contributes to individual states' likelihood of survival?

This paper uses a computer simulation to test competing answers to these questions, within the realist framework. Simulations obviously lack the theoretical heft of a true experiment, or even an observational study. The purpose of the simulation is to clear up intra-realist confusion, to establish internal consistency.

Much of this study is based on work done by Thomas R. Cusack and Richard J. Stoll some decades ago. The project culminated in a book (Cusack and Stoll 1990b), although the present work most closely parallels Stoll (1987). Their simulation is in turn based on an even older project (Bremer and Mihalka 1977).

The simulation was written in Python 3. Code and simulation records are available at <https://github.com/benhorvath/statesim/>.

The next section introduces the concept of state systems for readers unfamiliar with international relations theory. From there, I briefly describe the mechanics of the simulation. The results of 1594 runs are then analyzed with parametric survival analysis.

2 States and State Systems

For our purposes, we can define a state as a singular entity that controls a body of territory, along with the associated resources and population. A state has a monopoly of force within this territory; no greater authority exists. Legally, it is ‘equal’ to all other states. A state attempts to reproduce



Figure 1: Ancient Greek state system c. 700 BCE

itself by adhering to the dictates of its circumscribed reason. What states are trying to maximize depends on the theorist—security or power, variously.

A *state system* is thus a collection of such states, the relationships between them including *de jure* and *de facto* rules of conduct, and how power is distributed across them.

The example of ancient Greece should suffice as an illustration. Urban settlements began in Greece in the 8th century BCE, following a three century dark age. By 700 (Figure 1) the state system was composed of 24 states (Cusack and Stoll 1990b, 17).

The size of the system increased with new territory, until it reached its peak with 40 states in 430 BCE (Figure 2), just as the Peloponnesian War started.

By 338 BCE, the Greek system had collapsed into *universal empire* (Figure 3). Philip II of Macedon was able to establish control over all Greek states. The *plurality* of the system was destroyed, leaving one state as master of all. Philip died unexpectedly, and his son Alexander the Great lead the Greeks against the Persian empire and beyond.

The Greek system retained its multipolar character for almost 500 years, before collapsing into universal empire. Is a universal empire the final



Figure 2: Ancient Greek state system c. 430 BCE



Figure 3: Ancient Greek state system c. 338 BCE

result in any state system? What dynamics speed up or slow down this consolidating process? Relatedly, what explains the ‘lifetime’ of individual states? What mechanisms or even policies can be employed to prevent universal empire and state death?

This study examines a number of hypotheses around these questions. In particular, I examine the effects of:

- Inequality of power
- Uneven economic growth
- The existence of norms of restraint
- Accuracy of estimation
- Destructiveness of warfare
- Distribution of losses in warfare

3 The Simulation

The state system is represented by a *regular random* graph network, portrayed in Figure 4. Each node of the graph is a state and each edge represents a border. These networks have two parameters: n , defining the number of nodes (states), and p , defining the number of edges ('borders') between them. For all simulations in this paper, I have set $n = 98$ and $p = 8$. Although it is easy to configure these values in the simulation, this paper does not investigate their effect.¹

The simulation begins by initializing the ‘world.’ The configured parameters are loaded, generating the graph network, and each state is endowed with a level of power. Initial power distribution is modeled as a normal distribution with $\mu = 10$ and standard deviation parameterized in the config file.

After creating the world, the simulation occurs over a number of iterations (`niter` parameter, usually 1000) that follow four phases:

1. Select a ‘protagonist’ state that is the focus of the turn
2. Diplomacy

¹This representation is probably the greatest difference from Cusack and Stoll. They represented the state system on a hexagonal grid, with 98 cells. States on average border six other states. Part of the warfare process involves states capturing parts of other cells from vanquished enemies. See below on the ‘Versaille rule’ for how I attempt to account for this.

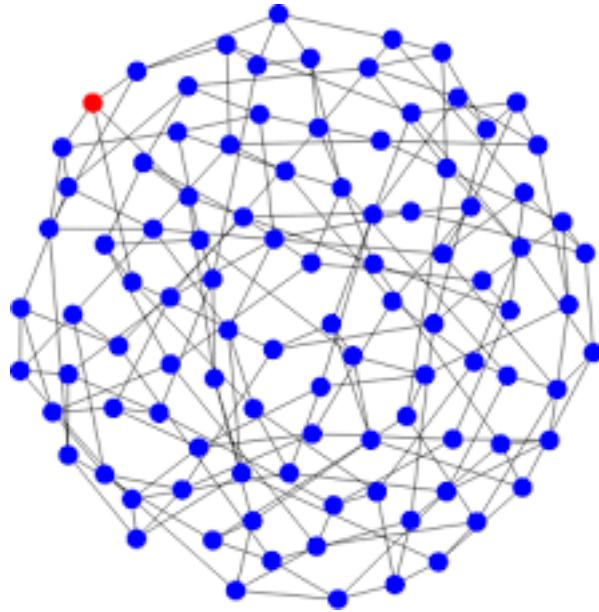


Figure 4: A random regular graph, governed by n , the number of nodes, and p , the number of connections between each node.

3. War (potentially)
4. Power adjustment

3.1 Phase 1: Select the ‘protagonist’ state

The turn’s protagonist is selected at the beginning of each turn, randomly but in proportion to its overall power. That is, more powerful states will have more opportunities to press their advantage in the international system.

3.2 Phase 2: Diplomacy

The selected state examines all the other states it borders. It calculates the power differential between itself and them. As in real-life, this calculation is not entirely accurate. It is possible for a state to over- and underestimate its advantage relative to other states. If we let $E_i(p_{ij})$ indicate state i ’s estimation of state j ’s power:

$$E_i(p_j) = p_j \times (1 + \text{randnorm}(0, \sigma_{\text{perception}}))$$

It is this number, not the actual power level, a state compares its own power with.

After calculating its neighbors' power, the state selects for a dispute the neighbor it has the greatest power differential over. If the state estimates all of its neighbors are stronger than it, the turn 'ends' and the simulation skips over the diplomacy and war phases.

Next follows a series of alliance-building. The targeted state seeks out allies among the states that border the protagonist. The protagonist state can attempt to build a counter-alliance, and then the targeted state has one more chance to expand its own alliance. The protagonist state has three opportunities to back down, to halt the aggression.

An important part of this simulation is how states evaluate the call for allies. The agents are very naive. Their only goal is to position themselves on the winning side, i.e., the side estimated to be more powerful. If a state views the offensive side as the most powerful, it will join the protagonist; if it judges the defensive side more powerful, it will join the targetted state. In all cases, states are estimating power with the impaired judgement described above.

3.3 Phase 3: War

Modeling warfare involves three issues:

1. Which state wins the war?
2. How are the costs of war distributed between the combatants?
3. How are the benefits, i.e., 'spoils of war,' distributed between the combatants?

3.3.1 Likelihood of victory

The outcome of a war between two states naturally relies on the power differential between them. We expect that on average states with more power should defeat states with less power. But there is still a role for chance, and in the history of warfare it is hardly rare that an 'objectively'

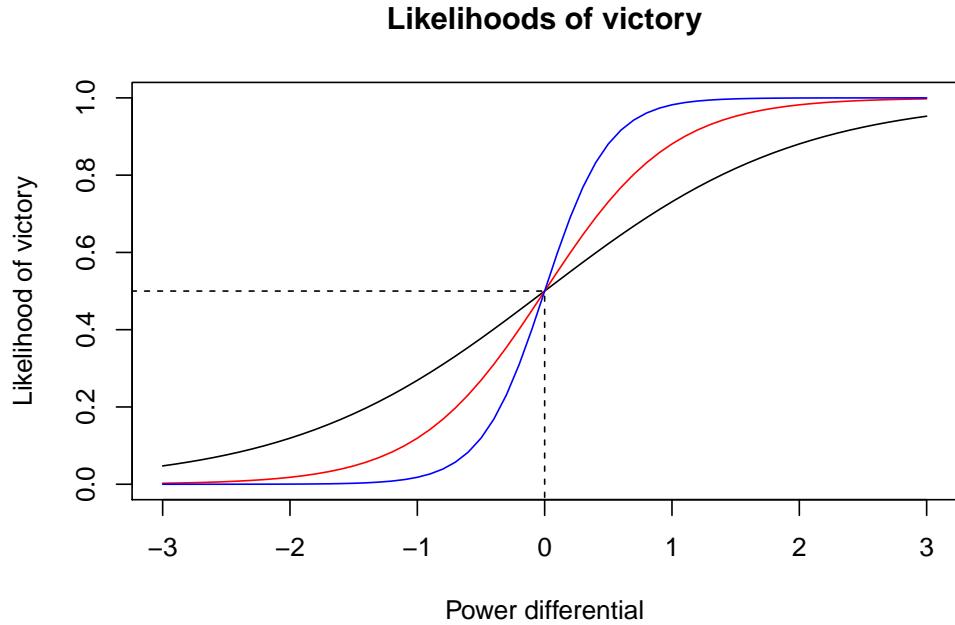


Figure 5: Likelihood of victory, where $\sigma_{\text{victory}} = (1, 2, 4)$ for black, red, and blue, respectively.

less powerful force prevails. Chance's weight versus material superiority is parameterized as σ_{victory} .

Likelihood of victory LV is modeled as a logistic function, where σ_{victory} controls the *steepness* of the curve. The figure shows curves for $\sigma_{\text{victory}} = (1, 2, 4)$ (black, red, and blue, respectively).

LV is exactly calculated as the area under the curve from negative infinity to the logged power differential. That is, state i's likelihood of victory over state j is (where $\sigma \equiv \sigma_{\text{victory}}$):

$$LV_{ij} = \frac{1}{\sqrt{\pi\sigma}} \int_{-\infty}^{\ln(p_i/p_j)} e^{-(x/\sigma)^2} dx$$

3.3.2 Costs of war

Both sides in a war incur a cost, but it should have three characteristics:

1. All sides should incur some cost in a war

2. The losing side should incur a higher cost than the winning side
3. The damage caused by a war increases as the power differential between the two sides decreases; thus wars between equal opponents are the most destructive

In the simulation, the maximum destructiveness wars can cause is controlled by C_{\max} . A war's *base* cost is calculated by:

$$C = \left(1 - \frac{LSR - 0.5}{0.5}\right) \times C_{\max}$$

where LSR is a ratio of the stronger side's power to the weaker side's power:

$$LSR = \frac{\max(p_i, p_j)}{p_i + p_j}$$

To ensure that the weaker side bears more cost than the stronger side, a modifier is added (in defeat) or subtracted (in victory) to the base cost:

$$C_{\text{stronger}} = C - (\min(\text{randnorm}(0, 1) \times C_{\max}, C_{\text{disparity}}))$$

$$C_{\text{weaker}} = C + (\min(\text{randnorm}(0, 1) \times C_{\max}, C_{\text{disparity}}))$$

These costs are assessed for all states, including those in coalitions.

3.3.3 Spoils of war

Finally, the winning coalition is allowed to seize some of the resources of the losing coalition. This is simply the reparations parameter times the total power of the losing alliance:

$$I = \text{reparations} \times p_j$$

This power forms a pot that is distributed to each member of the winning coalition, proportional to their power contribution to the coalition.

3.3.4 The Versailles rule

Stoll and Cusack's original simulation had the concept of territory. The leader of the losing side would surrender some of its territory to the members of the victorious coalition.

Since the present simulation has no concept of territory, I opted to create something with similar effects. The leader of the losing state transfers a percentage of its power equal to LSR to the winning side. Because this can be quite onerous on the losing state, I have termed it the Versailles rule.

It can be deactivated in any simulation run, and below I show that it has a very strong effect on the survival time of states and systems.

3.4 Phase 4: Power adjustment and economic growth

Once the diplomacy and wars are settled, states that no longer have any power are removed. Their 'borders' are passed to the conquering state and the map is redrawn.

Finally, economic growth needs to be simulated. Stoll and Cusack originally used a normal distribution with parameterized mean and standard deviation. This results in exponential growth over the run of the simulation, and economic depressions occur less frequently than they should.

To model economic growth more realistically, I draw growth rates from a Cauchey distribution. Negative growth in a single turn is capped at -30 percent, and positive growth is capped at 15 percent. Figure 6 compares a typical normal distribution with a typical Cauchey distribution.

4 Results

Ultimately, 1594 simulations were run, requiring about 24 hours of computer time. This represents 846,850 total turns, and 431,510 conflicts that ended in wars.

Most (1140) of the simulations ended in universal empire, or about 71 percent. This is substantially more than Cusack and Stoll report (1990b).

Figures 7 and 8 are close up view of a randomly selected simulation (ID number 20200516t231815). The former shows the relationship between

Normal and Cauchy PDFs

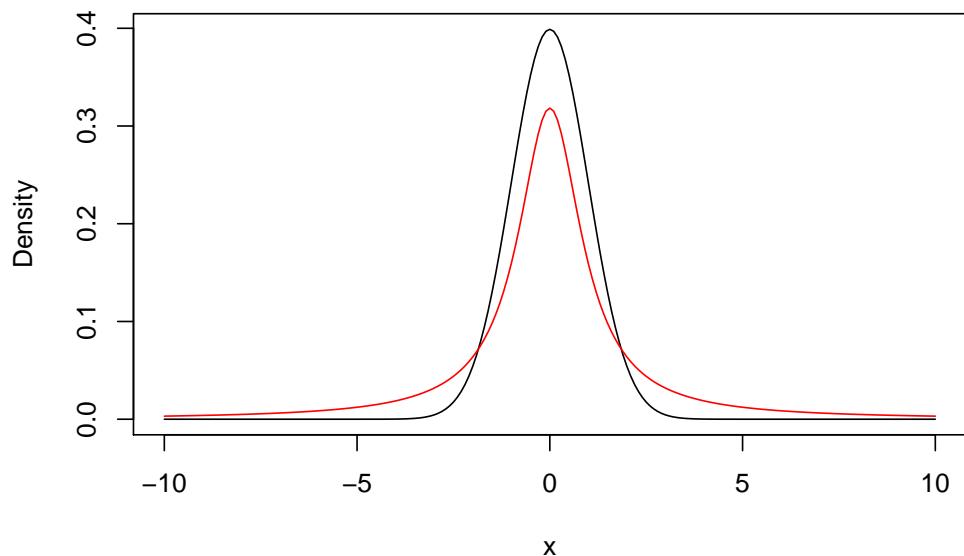


Figure 6: Cauchy (red) distributions has a thicker tails than the normal distribution (black), more realistically representing the probability of extreme events, like economic depression.

Simulation 20200516t231815: State survival

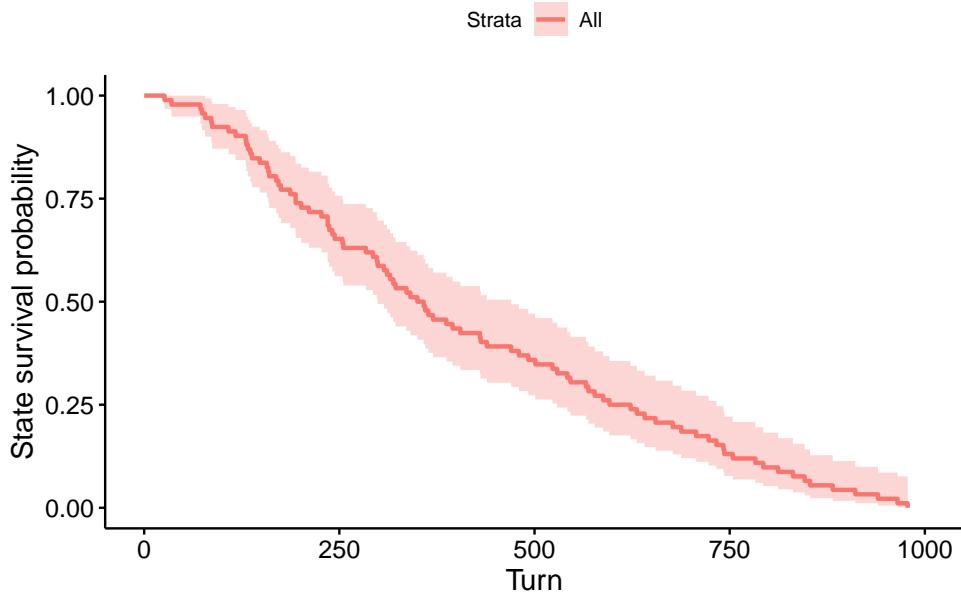


Figure 7: State survival probability for simulation ID 20200516t231815.

turn number and state survival, or the *hazard curve*. Fifty percent of states survive to turn 354 in this simulation.

Figure 8 shows how the distribution of state power varies over the course of the simulation. It is dominated by maximum power (orange), standard deviation (pink), and mean (red). It is clear that the dominant state becomes very powerful just before turn 750, naturally increasing the standard deviation. In contrast, the average increases very slowly.

4.1 State Survival

The next figure shows the Kaplan-Meier hazard curve for all states across all simulations. The median survival time is 144 turns, across all simulations.

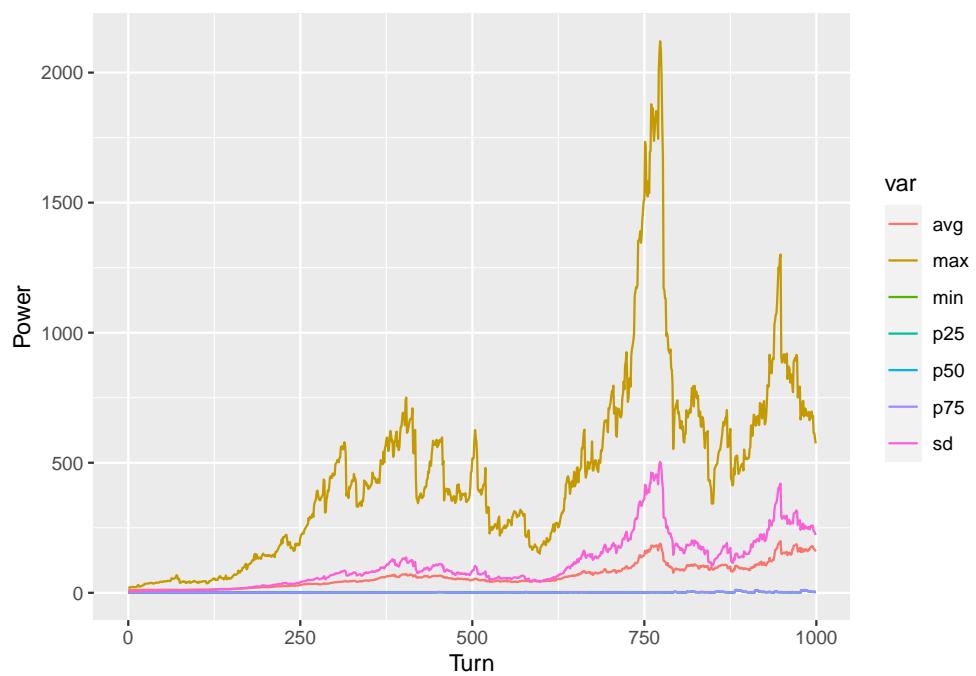
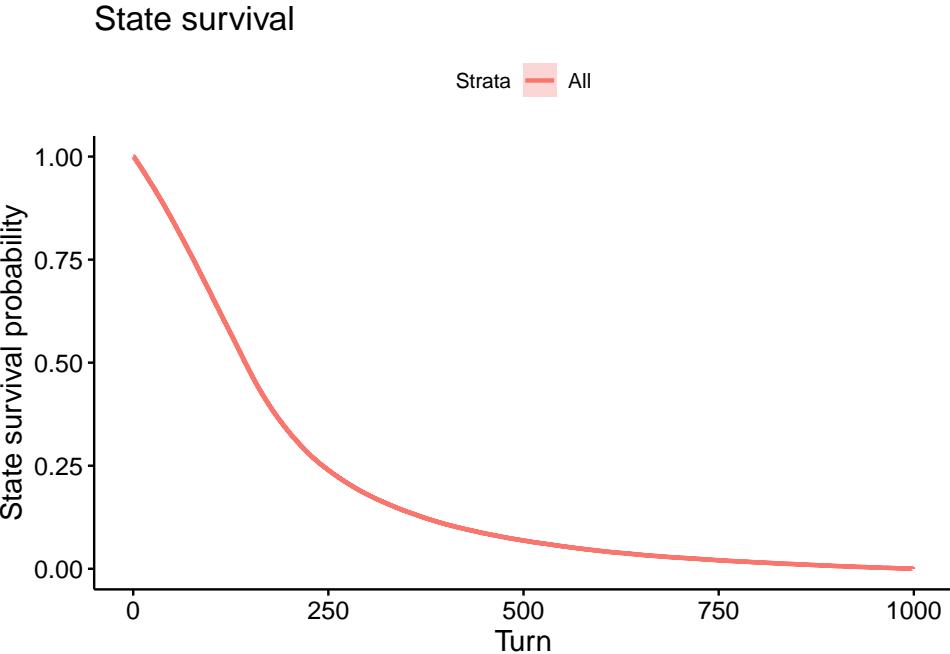


Figure 8: Distribution of power over simulation ID 20200516t231815, by summary statistics.



Parametric survival analysis is used to model the effect of the parameters. An exponential hazard curve is assumed. The estimated coefficients with standard errors are shown in the plot in Figure 9. Interpreting the plot is fairly simple: Where the error bar of the fitted parameter touches 1, the parameter is insignificant. All parameters are significant, though `power_dist_sigma` is closest to non-significance.

Parameters with estimates greater than 1 decrease the odds of state survival, while parameters with estimates below one increase the odds of state survival. ‘State survival’ can also be interpreted as ‘time to state death.’ Thus only `growth_mu` increases state survival, i.e., increasing the mean of the economic growth distribution improves states’ chance of survival. All other variables lower state survival.

We can examine the different survival curves for different values of these parameters. The impact of the Versailles rule is examined in Figure 11. With the Versailles rule activated, there is almost no probability the simulation will make it to turn 1000 without devolving into universal empire. With it off, this becomes a possibility, though not a great one. With the Versailles rule off, median state survival time is 222 turns; with it on, this shrinks to 116. This sheds light on the parameter estimate from the model being

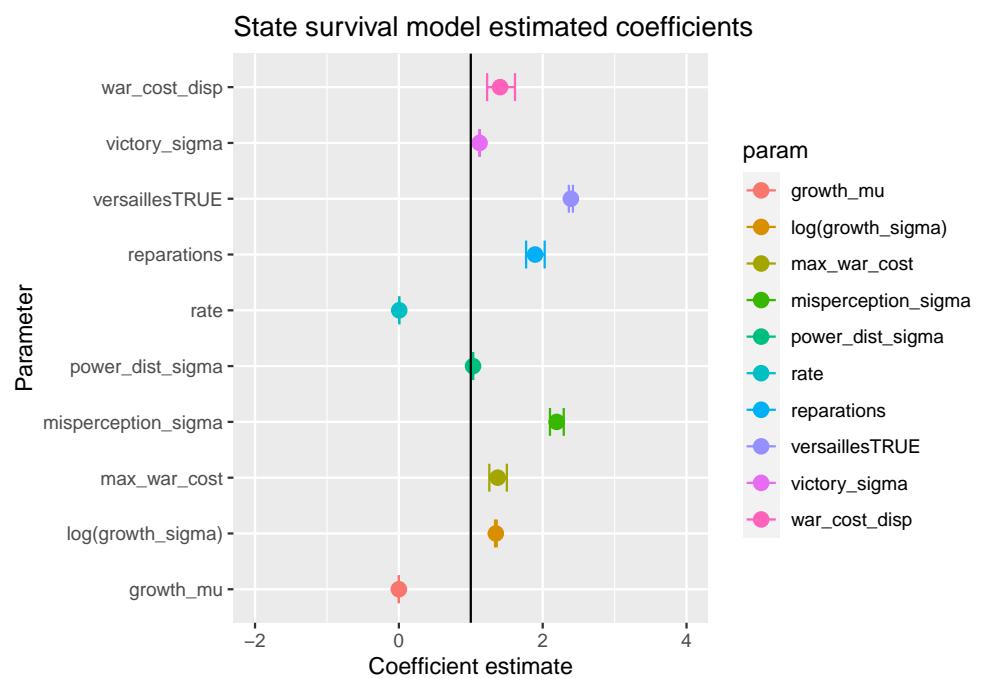


Figure 9: Estimated coefficients and standard errors of fitted model of state survival.

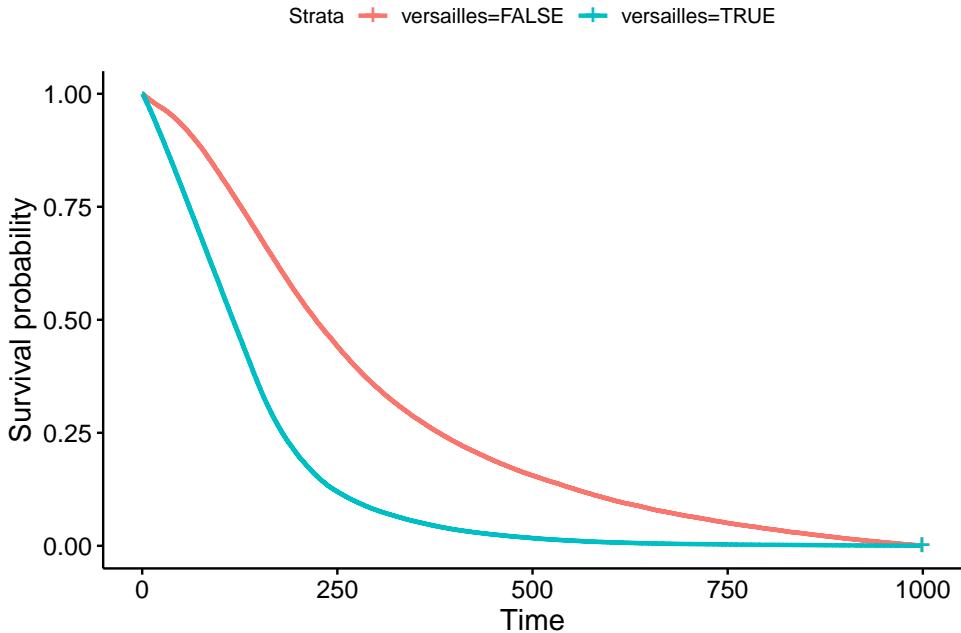


Figure 10: Survival time varies greatly depending on whether the Versailles rule is activated.

slightly more than 2.

To evaluate how well our model fits, plot the parametric hazard curve estimated by the model against the non-parametric Kaplan-Meier hazard curve (in red). We see there is strong alignment between the two, and conclude that the model fits the data reasonably well.

4.2 System Survival

We perform the same analysis above, but to estimate the turns to universal empire. The estimated coefficients and standard errors are plotted in Figure 12.

It's immediately obvious these standard errors are much larger than the model of state survival. War cost disparity, standard deviation of initial power distribution, and maximum war cost parameters all come up statistically insignificant. The Versailles rule has, again, a strong effect on system survival, along with reparations.

State survival model fit

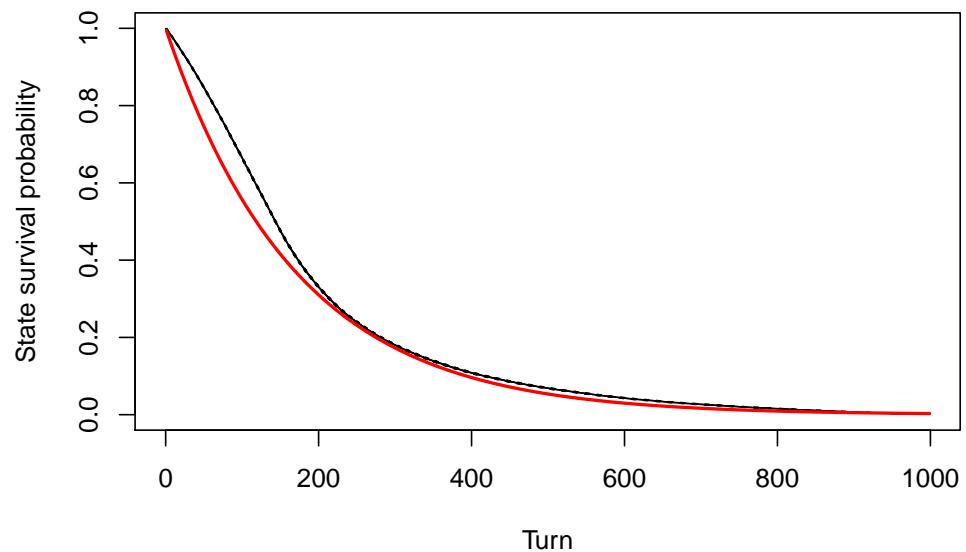


Figure 11: Parametric model (black) plotted against non-parametric fit (red). Close agreement between the two indicate the model fits the data well.

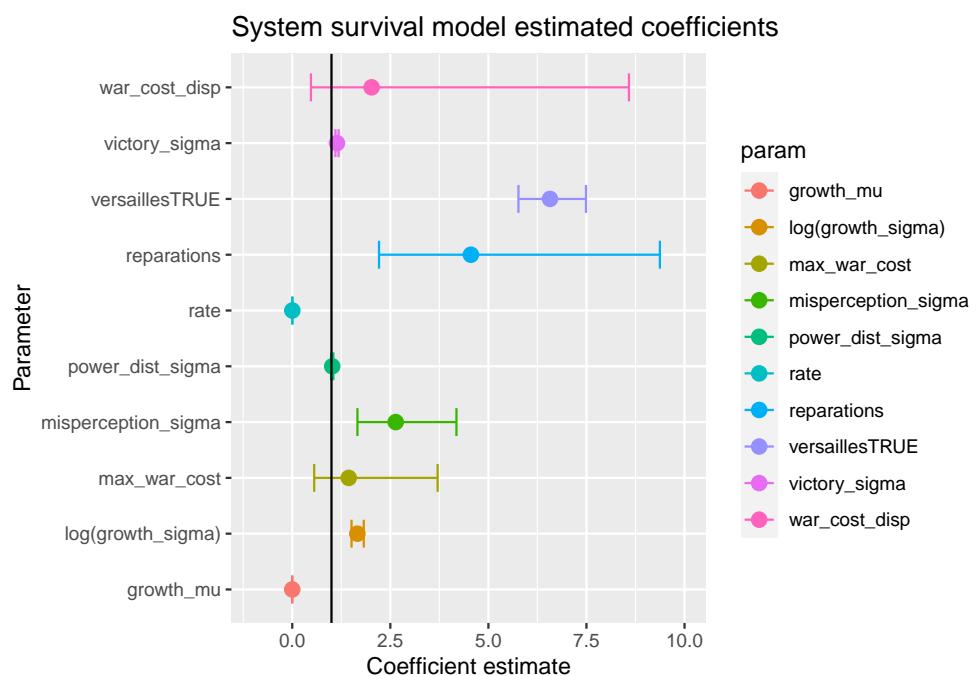


Figure 12: Estimated coefficients and standard errors of fitted model of system survival.

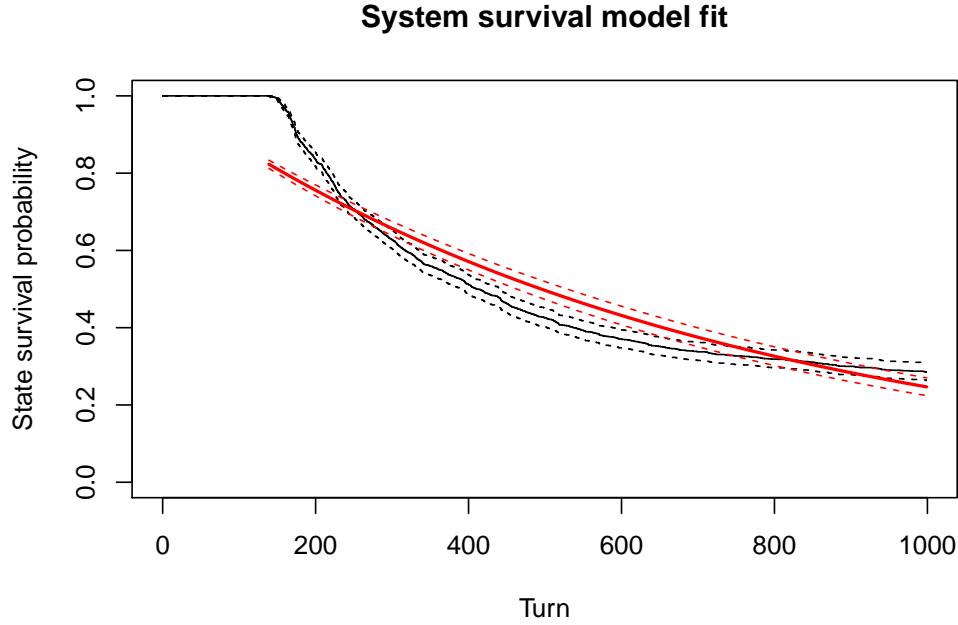


Figure 13: Parametric model (black) plotted against non-parametric fit (red). Incongruity between the two suggest the exponential model of state survival is a poor fit.

Plotting the exponential hazard curve fitted by the model against the non-parametric hazard curve shows substantial disagreement (Figure 13). This and the wide standard errors suggests the model does not fit the data well.

5 Conclusions

This experiment diverges from Cusack and Stoll's setup in many key ways. These include eliminating the concept of territory, modeling the world as a graph network, and the addition of more and different randomness. Nonetheless, the simulations broadly demonstrate Stoll and Cusack's point: That war reparations, war destructiveness, economic growth, etc., do have an effect on state and system survival. This is *contra* realist proponents of the 'automatic stabilization' theory of state systems. According to those theorists, none of the factors examined above should produce an effect on state or system survival. At the least, this simulation suggests such theories lack internal consistency.

6 References

For Python code and results of the simulation runs, see the author's GitHub page at: <https://github.com/benhorvath/statesim/>.

The key reference is Cusack and Stoll (1990b), which is in turn an extension of Bremer and Mihakla (1977). See Cusack (1990) for a short but comprehensive review of the research program, including extensions of the base simulation.

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