Recognizing 'Game Changers' in Extrapolation Models: An Application to Counterinsurgency

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RECOGNIZING ‘GAME CHANGERS’ IN EXTRAPOLATION MODELS: AN APPLICATION TO COUNTERINSURGENCY

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A Thesis

Presented to

the Faculty of the Josef Korbel School of International Studies

University of Denver

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In Partial Fulfillment

of the Requirements for the Degree

Master of Arts

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by

Micah Dolcort-Silver

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Advisor: Dr. Erica Chenoweth
Abstract

Recent empirical studies suggest insurgencies may be accurately described by aggregated extrapolation models, such that past behavior becomes the best predictor for future action. I argue that aggregated extrapolation models possess two flaws that make it a poor choice for examining insurgencies. First, aggregated extrapolation models ask the wrong question. The more interesting question is to ask when present action is no longer explainable by past behavior. Secondly, aggregate models mask changes that a phenomenon undergoes over time which are only revealed upon disaggregating the data. Starting with a model and findings provided by Neil Johnson, I use casualty data from the Iraq War to offer an alternative method to identify changes in the phenomenon under observation with the addition of no new data. Presenting an alternate set of findings, I propose it is possible to identify ‘game changer’ events with the introduction of breakpoints to observe for distinct departures from the baseline trajectory.
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CHAPTER ONE: INTRODUCTION

In the fall of 2010, American soldiers with the 10th Mountain Division gained a foothold into a Taliban-controlled area in the northern Afghanistan province of Kunduz. Anecdotal reports from soldiers involved in the operation relayed accounts from their Afghan National Army partners entering villages in this once enemy-controlled territory with tears in their eyes, some returning home for the first time in many years. Upon completion of the initial clearing operations, the soldiers constructed a combat outpost (COP) to serve as point of departure for future coalition operations in the area.

While the majority of fighting was accomplished during the initial phase of the operation, Taliban fighters capable of conducting harassing attacks remained scattered throughout the area. Within 72 hours of setting up the COP, soldiers reported receiving indirect fire from enemy mortars. Over the next 48 hours, soldiers reported enemy mortar fire repeatedly occurred between the hours of 1200-1300z from a location northwest of the COP. Furthermore, the mortar rounds were impacting closer to the COP with each attack. The Taliban mortar team was improving their aim. Although no soldiers had yet been injured by the indirect fire, the commander assessed it was only a matter of time before the mortars found their mark.

The intelligence team supporting the operation accurately identified the enemy’s consistent pattern in both time and space for conducting these mortar attacks. Having extrapolated out what the enemy action was likely to be during the next 24-hour period,
the intelligence team supported a mission to position a weapon system in the target area during the time period in which the Taliban were expected to attack. In this case, past behavior was the best predictor of future enemy action. Two enemy fighters entered the area previously identified for enemy mortar attacks and were observed uncovering a mortar tube hidden in a nearby culvert. At this time, all enemy fighters and the mortar tube were destroyed before being able to conduct another attack on the US-Afghan COP.¹

This story reinforces what has become a conventional approach to understanding counterinsurgency and is reinforced by recent empirical work.² Tactical engagements between insurgents and coalition forces play out as extrapolations until one side recognizes the pattern and temporarily disrupts the trajectory. But, here is the problem. The instances that matter most are those when present action is no longer explainable by past behavior. Elsewhere, these times have been described as strategic surprise.³

In the winter of 2010, also in Kunduz Province, Taliban forces successfully executed a spectacular attack targeting the Afghan National Army recruiting center

¹ Both this incident and the Kunduz Afghan National Army Recruiting center attack are based on personal observations from author’s deployment to Northern Afghanistan (Regional Command – North) with 1st Brigade Combat Team (BCT), 10th Mountain Division from March 2010 to February 2011.

² For further examples of recent empirical approaches to irregular warfare, see “The Science of Civil War: What Makes Heroic Strife” 2012. See “Cry Havoc! And Let Slips the Maths of War” 2011 for an overview of Neil Johnson’s Red Queen Hypothesis model discussed in this paper.

³ There are, perhaps, two truisms for strategic surprise when discussing intelligence activities. First, such surprises are not the absence of information but rather the absence of analysis. Calls for post-mortem investigations concerning intelligence failures often begin with the question, “how were we taken by surprise?” During these after-action reviews, much attention is given as to whether available information could have been sufficiently analyzed to better prepare for the resulting surprise. It is Robert Jervis who notes intelligence failures are closely observed orphans, important, but “as misunderstood as they are berated.” The second truism is that surprise is inevitable but responses are optional. How an individual, or nation, chooses to respond largely plays into the consequences from the inevitable surprise. See Jervis 2010, Handel 1984, Betts 1981.
located within Kunduz City.\textsuperscript{4} Suicide bombers attacked the outer perimeter while enemy fighters temporarily gained control of the recruitment center in the provincial capital. Previous coalition intelligence assessments had not extrapolated this attack as a likely scenario based upon past insurgent behavior. Coalition forces did not see this attack coming based upon observations of previous insurgent activity in the province. Nor would the recent scholarly literature concerning the empirical study of counterinsurgency operations have captured the tactical innovations demonstrated by the Taliban forces during this particular attack in the winter of 2010. At this particular point in time, present action was no longer explainable by past behavior.

These two stories from Kunduz Province capture the host of challenges and opportunities presented to the United States Armed Forces and Intelligence Community (IC) over the past ten years of armed conflict across two theaters of operations and global mission requirements. Assessing likely adversarial action remains central to the ability to deter and defeat the enemy. Terrorists and insurgents, be they organized networks, local groups or individuals do not, however, conduct operations in accordance with something akin to a Soviet order of battle. Herein lies the current challenge. How to properly forecast the activities of enemy groups and individuals operating independently across disparate geography?

Meteorologists, seismologists and intelligence analysts face a common set of challenges across their respective disciplines in modeling future outcomes. Forecasting a hurricane’s path, the likelihood of future tectonic plate shifts in a given area, and an impending terrorist attack all rely upon models. Models are formed as representations of

\textsuperscript{4} This attack is also based upon author’s personal observations. For further reading, see Rivera and Rahimi 2010.
reality absent those parts deemed irrelevant to the empirical phenomenon under observation.\(^5\)

While there exists a host of available forecasting methods, this paper focuses specifically on aggregated extrapolation models. Extrapolation models are widely used across disciplines and are considered “reliable, objective, inexpensive, quick, and easily automated.”\(^6\) Aggregated extrapolation models, in particular, are seen as advantageous for their ability to forecast a smooth trend line less sensitive to the irregularities presented by individual data points.\(^7\) For these reasons and others, forecasting in general and extrapolation models in particular have become popular policy instruments.\(^8\) While described as a “statistician’s delight,” they are, however, often times wrong.\(^9\)

This paper begins with presenting two flaws inherent in aggregated extrapolation models and proceeds to offer one proposed solution. The theoretical assumption driving all extrapolation models is that past behavior is the best predictor of future action.\(^{10}\) It is, in effect, to establish a baseline trajectory for a given phenomenon under observation based upon historic trends. The first flaw is apparent when considering the policymaker’s dilemma, whose task it is to address circumstances arising from change while being presented with a tool constructed to convey continuity. Instead, from the

\(^5\) Frankfort-Nachmias and Nachmias 2007, 39-40

\(^6\) Armstrong 2001, 217

\(^7\) Ibid., 223


\(^9\) Armstrong 2001, 218

\(^{10}\) Armstrong 2001, 218
policymaker’s perspective, the more interesting question is to ask when present action is no longer explainable by past behavior. In effect, it is to ask how to recognize a ‘game changer’ before it occurs? Here, ‘game changers’ are those instances where the trajectory breaks down and present action is no longer explainable by past behavior. The inherent problem with ‘game changers’ is that their impact only becomes evident after the phenomenon under observation has undergone change, usually manifesting itself in the form of a crisis. As equally interesting as the strategic surprise spurred on by the 2011 revolutions in Tunisia, Egypt, and Libya was the completely absent assessment to the contrary of the established trajectory for these respective regimes.\textsuperscript{11} Establishing a baseline trajectory remains a necessary step for understanding normal behavior for a phenomenon under observation. It is only in establishing this baseline that it then becomes possible to engage in the more policy-relevant question of identifying impending change.

The second flaw proposes aggregated extrapolation models mask changes that a phenomenon undergoes over time which are only revealed upon disaggregating the data. In short, the aggregation used to present a smooth trend line for the phenomenon under observation is misleading. Aggregation may occur incidentally or temporally, however, the impact is the same.\textsuperscript{12}

Here, crime statistics provide a useful illustration. The Federal Bureau of Investigation reported in 2011 that violent crime across the nation was on a downward

\textsuperscript{11} Ajami 2012

\textsuperscript{12} Stephen Shellman brings to light the lack of attention paid within political science to how temporal aggregation affects results. See Shellman 2004
trend by 3.8% when compared to the previous year.\textsuperscript{13} Looking at five- and ten-year trends, violent crime was down 15.4% from 2007 levels and 15.5% from 2002 levels.\textsuperscript{14} As such, an extrapolation model for documented violent crimes in the United States aggregated annually would show a steadily declining trajectory over time. Addressing the first flaw in aggregated extrapolation models proposed in this paper, this steadily declining trajectory fails to address the most policy-relevant question for those concerned with violent crime in the United States. Where in America is violent crime on the rise? Or, put another way, where is present action not explainable by past behavior?

Addressing the second flaw, disaggregating the incidents of violent crime down to the state level reveals New Hampshire reported a 12.4% increase in violent crime for 2011.\textsuperscript{15} Another method for examining violent crimes using the existing data would be to disaggregate temporally, perhaps down to monthly or weekly data resolution instead of annually. While this time series data is unavailable through the FBI website, the date of incident for each violent crime reported is certainly documented. Temporally disaggregating violent crime data would reveal both annual trending patterns, some months likely experience more violent incidents than others, as well as ‘game changer’ events. Sudden spikes or drops in violent crime are masked in the temporally aggregated model, eliminating opportunities to identify changes in the phenomenon under observation.

\begin{thebibliography}{9}
\bibitem{13} "Federal Bureau of Investigations: Crime in the United States 2011, Table 4" 2012
\bibitem{15} "Federal Bureau of Investigations: Crime in the United States 2011, Table 4" 2012
\end{thebibliography}
Recognizing these two inherent flaws for aggregated extrapolation models, this paper proposes that it is possible to identify changes in the phenomenon’s trajectory, ‘game changers’, before the crisis occurs. It does not attempt to provide the causal origins for why the phenomenon is changing, the narrative of which is likely unique to each situation. Instead, this paper offers an alternative method for using existing aggregated extrapolation models to identify changes in the phenomenon under observation with the addition of no new data. This last point is significant in that it suggests that impending ‘game changers’ are identifiable strictly by altering the extrapolation model’s construction.

This paper will trace the policy, methodological and theoretical implications for exploring how to recognize a ‘game changer’ in extrapolated models. While the more complete discussion on a decision-maker’s perception of the world and the operational environment a given policy will be executed in is addressed elsewhere, it is useful for the purposes of this paper to focus on the first part of this question.16 Where does a decision-maker’s perception of the world originated from? Models themselves represent a given perception of the world, where certain driving forces are amplified at the expense of others considered irrelevant to the representation of reality being captured. Therefore, the policy implications for a model, one extrapolated as is the focus for this paper, are significant for the reasonable belief that they influence the decision-maker’s perception of the world. The methodological implications are concerned with how the extrapolated model is constructed. As this paper will demonstrate, it is important to not only identify which driving forces are relevant to the phenomenon under observation but how they are

16 Jervis 1976, 13-14
to be structured to act within the model. Theoretical implications will address scholarly literature on forecasting across illustrative domains and how these writings shape the understanding for a given phenomenon’s change over time.

Chapter 2 contains a broad overview of the relevant literature on the use of aggregated extrapolation models across disciplines. Particular attention is given to meteorology, seismology and strategic intelligence to illustrate the implications brought forth in how such a model is structured, tested and used. In doing so, different forms of forecasting will be addressed across disciplines with an emphasis on common challenges present in each respective field. This chapter will conclude with a discussion on how recognizing ‘game changers’ as breaks in the established trajectory need not require understanding its causal origins to be useful, but only that impending change is likely along the phenomenon’s baseline.

In Chapter 3, Neil Johnson’s Red Queen Hypothesis is presented and critiqued. In 2011, Johnson offered up a solution to the policy relevant question for determining the next attack with an extrapolated model constructed from casualty data for the wars in Afghanistan, Iraq and several terrorist campaigns. In doing so, he concludes an insurgency’s trajectory is based solely on the dynamic relationship between insurgents and coalition military forces as measured by the frequency and escalation of hostile attacks. In effect, Johnson proposes insurgent and coalition military interactions are analogous to the Red Queen Hypothesis as presented by evolutionary biology and penned by Lewis Carroll in Through the Looking Glass. In presenting Johnson’s work, this paper

17 Johnson et al. 2011b
will structure critiques along the policy, methodological and theoretical implications brought forth by Johnson’s model.

Ultimately, this paper rejects the major findings offered by the Red Queen Hypothesis and proceeds with an alternate study presented in Chapter 4. Using the same model and data described in the previous chapter, Chapter 4 begins with a novel research design for exploring how to recognize impending ‘game changers.’ Introducing distinct breakpoints into the Red Queen Hypothesis demonstrates how temporal aggregation influences the overall results. In effect, the alternate study design proposed and executed here provides an alternative perspective on the same phenomenon under observation using identical datasets. This research design examines hostile attacks for nine individual Iraqi Provinces between 2003 and 2010 across two phases, each phase being characterized by a distinct breakpoint. Of note, two categories of breakpoints are examined in this study. Indications-driven breakpoints are introduced based on observable changes in the phenomenon. For reasons that will be explained in greater detail in Chapter 4, the indications-driven breakpoint is established based upon the minimum value attained by the cumulative moving average for the frequency in hostile attacks. An event-date breakpoint, however, is established at a given point in time deemed relevant to how the phenomenon progresses in the future. For purposes of this

\[18\text{ Iraq has a total of 18 provinces, however, only nine are examined in the original study or the alternate research described in this paper.}\]
study, an event-date breakpoint is established at 1 January 2007 to capture the decision to increase troop levels in what has become popularly known as “The Surge.”

In chapter 5, results and implications are discussed based upon the alternate study described in the previous chapter. Of note, three main findings are presented. First, the study’s results show that the Iraq Insurgency behaved differently during periods of escalation and de-escalation. Secondly, the results demonstrate sub-national variance across individual provinces in Iraq. Thirdly, there appears to be a scale invariant nature for how hostile attacks escalate that is independent of a particular weapon system. Introducing distinct breakpoints revealed departures from the baseline trajectory established by the aggregate extrapolation model. The key implication is that introducing distinct breakpoints allows for novel findings to be derived that would otherwise be masked when the phenomenon is viewed in aggregate.

In chapter 6, the paper concludes by considering the consequences for the overall policy, methodological and theoretical implications regarding the alternate study presented in this paper. After reviewing the findings discussed in Chapter 5 for what can be definitively concluded, policy-relevant claims are put forth that form the basis for a future research agenda. Here, preliminary findings are presented for examining the Afghanistan Insurgency following the methodology used in the alternate study. In summarizing the discussion on recognizing ‘game changers,’ this paper will offer recommendations for how to best utilize the knowledge of impending change.

19 President George W. Bush’s 2007 troop level increase is commonly known as “The Surge” and involved adding an additional five brigade combat teams to forces fighting in Iraq. See Bush 2007. For an overview of how these military forces were employed as part of a larger strategy beginning in 2007, see Kagan 2009.
CHAPTER TWO: LITERATURE REVIEW

The purpose of this chapter is to explore the logic of using aggregated extrapolation models for the purposes of forecasting across disciplines. In discussing forecasts across meteorology, seismology and intelligence this section will construct the policy, methodological and theoretical implications relevant to the particular extrapolation model examined in this paper. Examining meteorology, this paper will trace the theoretical discussion regarding the transition from ‘deterministic short-range numerical weather prediction (NWP)’ to a stochastic-dynamic view widely practiced today. A review of seismology will emphasize the methodological implications and challenges when developing useful forecasts with models based upon past events. Lastly, intelligence provides a useful domain for illustrating the policy implications for using extrapolation models to identify ‘game-changer’ events that signify a point of departure from an established baseline trajectory along an alternate path.

Meteorology

The key goals ascribed to meteorology are the “complete understanding and accurate prediction of atmospheric phenomena.”¹ While the methods and technology have evolved over time, the goals remain the same. In exploring meteorology as an illustrative domain for extrapolation models, this section will highlight how

¹ “Glossary of Meteorology” 2000, 489
methodological developments were driven by theoretical evolutions and conclude with the relevant policy implications.

Within the United States, a total of nine centers comprise the National Centers for Environmental Predictions (NCEP) under the auspices of the National Weather Service (NWS) charged with producing national and global meteorological forecasts. Each weather center has a specific forecasting mission; the Storm Prediction Center addresses “tornado and severe weather” while the Aviation Weather Center forecasts “hazardous flight conditions.” The National Weather Service is aided in its task by an IBM supercomputer tasked with parsing and shaping the big data into manageable chunks for the meteorologists. The technological advances and computing power have led some to declare both theory and the scientific method to be obsolete. The current state of meteorology, however, provides a convincing counter-argument. Determining one’s behavior based upon the expected weather is, perhaps, the most common interaction a person has with incorporating forecasts into their own lives. Yet, the weather is frequently not what it is forecasted to be. Put another way, data alone isn’t enough to forecast.

Initial efforts at weather forecasting relied upon deterministic aggregated extrapolations. In short, weather forecasts were determined based upon comparing

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2 “About NCEP” 2012

3 Silver 2012b

4 “The End of Theory: The Data Deluge Makes the Scientific Method Obsolete” 2013
present weather conditions for a given time and space to historic patterns. Past behavior was considered to be the best predictor for future action. In pointing to the limits for such modeling, Nate Silver retells an account in which over one hundred children died of hypothermia in Topeka, Kansas. Here, he notes, having the average temperature for a winter day is not useful for addressing sudden blizzard conditions which ultimately led to the children’s deaths. Silver’s recounting of this story is but another example highlighting the two flaws in aggregated extrapolation models. Aggregating weather conditions fails to identify the most relevant question in identifying discontinuity, manifested here in a sudden blizzard, and is, furthermore, misleading in that it masks the changing nuances in weather over the course of a given month.

Dissatisfaction with what deterministic aggregated extrapolation had to offer meteorology led to one of its great theoretical advances. Lewis Fry Richardson opens the preface to what became his seminal work in meteorology, *Weather Prediction by Numerical Process*, with an assessment for the current state of affairs in his chosen field. Describing the process by which current weather conditions are compared to past conditions in the same geographic area under observation, Richardson notes that the “past history of the atmosphere is used…as a full-scale working model of its present self.” This process was not intellectually satisfying for Richardson, who proceeded to develop a

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5 In the preface to his seminal work on meteorology, *Weather Prediction by Numerical Process*, Richardson describes this method such that “past history of the atmosphere is used…as a full-scale working model of its present self.” Richardson 1965, xi

6 Silver 2012b
novel methodology largely inspired by how differential equations were incorporated into the *Nautical Almanac*.\(^7\)

Two important points are worth noting here. First, Lewis Fry Richardson offers a unique conceptual bridge for the purposes of this paper. Not only does his work in meteorology provide a useful illustrative domain for aggregated extrapolation models, in general, but his later work on the study of deadly conflict informs the specific model examined in this paper.\(^8\) Secondly, Richardson’s contribution described here was not an immediately accessible and applicable method for weather forecasting. Instead, his work is known for providing the theoretical foundations for a dynamical approach to meteorology years before the technological innovations in computers would make the work feasible.\(^9\) The ‘forecasting factory’ first imagined by Richardson is manifested in today’s meteorological centers.\(^10\) As noted earlier, weather forecasts are improving in accuracy over time.\(^11\) The policy implications for this are clearly evident when examining government responses to severe weather conditions.

\(^7\) Richardson 1965, xi

\(^8\) Richardson’s work on armed conflict will be explored in greater detail later in this paper. See Richardson 1960, Clauset, Young and Gleditsch 2007.

\(^9\) After a failed attempt to accurately deduce weather conditions for a past date using his methodology later captured in *Weather Prediction by Numerical Process*, Richardson described what he imagined would be needed to accomplish the necessary computations. By his own estimations, some 64,000 computers with an ability to calculate “perhaps ten times faster than he himself had done” would be required. Richardson 1965, vi-vii.

\(^10\) Cox 2002, 157

\(^11\) Here, accuracy is defined as comparing the weather forecast with observed weather conditions. See Silver 2012a, 131-132 or Eric Floheher’s weather forecast accuracy website www.flohehrs.com, Flohehrs 2012.
Preparations for Hurricane Sandy were made possible because of the most state-of-the-art weather forecasting available coupled with updated lessons in emergency management practices.\textsuperscript{12} Even still, the estimated cost to the Northeastern United States following the storm are estimated at $20 Billion for property damage alone.\textsuperscript{13} Were the storm to hit landfall without prior warning and preparation, the costs would have been significantly more damaging. Here, meteorology may provide one last useful lesson regarding forecasts and extrapolation models. They can and do improve with time.\textsuperscript{14}

Seismology

In spite of the USGS official position that discounts the possibility for accurately predicting future earthquakes, there are several ambitious efforts to do so. One such endeavor is the Collaboratory for the Study of Earthquake Predictability (CSEP). The CSEP is interested in two key objectives that broadly relate to this paper’s examination of extrapolation models. First, CSEP seeks to address how to best conduct and evaluate “scientific prediction experiments.” Secondly, CSEP is interested in the intrinsic predictability for the earthquake rupture process.\textsuperscript{15} Similarly, this paper is interested in how to best identify future outcomes and explores a possible method based upon the intrinsic predictability for the phenomenon under observation—in this case, hostile attacks in Iraq.

\textsuperscript{12} Samenow 2012
\textsuperscript{13} “Superstorm Sandy: Facts About the Frankenstorm” 2013
\textsuperscript{14} Kerr 2012
\textsuperscript{15} “Collaboratory for the Study of Earthquake Predictability” 2012
A leading approach for earthquake prediction can be placed under the category of “pattern-recognition techniques.” Following the same mantra for extrapolation identified in this paper’s introduction, pattern-recognition techniques operate under the assumption that past behavior is the best predictor for future action. The question then becomes a matter of determining which past behavior is, in fact, the key driving force for extrapolating future events. Or, put another way, what patterns are relevant for predicting an earthquake outcome? It is at this decision point in which the seismology field remains divided. Contending prediction models for identifying the next big earthquake have at various times proposed that a calm before the storm, or “precursory quiescence,” and heightened activity, or “precursory upsurge,” serve as useful predictors. Accounting for both is contradictory. Yet, each case proceeded from a positivist methodology and, therefore, some form of observation into the key driving forces deemed relevant to the target phenomenon. This points to one obvious and important principle for extrapolation models, which is to use domain knowledge in structuring the forecast. Domain knowledge is a subset of contextual information and is comprised of the explanatory factors responsible for influencing a forecast. Conflicting accounts regarding which variables are explanatory factors, as is the case in seismology, leads to the diversified approaches in attempts to extrapolate the phenomenon over time.

Another key principle that relates to prediction models generally is that there must be a method for determining how useful a given model is in forecasting future events.

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16 Hough 2010, 142

17 Armstrong 2001, 221

18 Ibid., 774
Described elsewhere as being concerned with “wins and losses,” critics of earthquake prediction point to the field’s losing record by way of discounting current methods.\(^{19}\) The Keilis-Borok method is one such model that gained notoriety for its supposed winning streak, only to later come under scrutiny when its record was more closely examined. Vladimir Keilis-Borok led the development of the M8 algorithm that identifies regional seismic activity as a key driving force for future seismic activity.\(^{20}\) While the Keilis-Borok method is sufficiently complex, its central proposition is that past seismic activity is the best predictor of future seismic activity. Keilis-Borok gained notoriety for his prediction of the 1989 Loma Prieta earthquake. Critics of earthquake prediction point to the limited utility in methods that accurately identify historic events, sometimes called ‘postdiction,’ but are incapable of predicting future events.\(^{21}\) What made Keilis-Borok’s 1989 prediction significant for many is that he did so prior to the earthquake striking Loma Prieta. The question remained, however, whether Keilis-Borok’s prediction was one of scientific technique or luck.\(^{22}\) Since the 1989 prediction, an evaluation of the track record for Keilis-Borok’s methods identified only four positive hits out of twenty-four predictions.\(^{23}\)

Although a statistical bust, the Keilis-Borok method provides several methodological implications that speak directly to this paper’s conversation on the two

\(^{19}\) Silver 2012a, 77

\(^{20}\) Hough 2010, 143

\(^{21}\) Ibid., 145

\(^{22}\) Kerr 1991

\(^{23}\) Zechar 2008, 4
flaws for aggregated extrapolation models. Attempts at earthquake prediction, although demonstrated here as inconclusive, directly address the first flaw by searching for discontinuity. Earthquakes are, in effect, those instances whereby present action breaks from past behavior. The Keilis-Borok method avoids the second flaw in that it does not aggregate temporally or across event data. Two additional methodological lessons taken from seismology are worth reiterating here. First, domain knowledge shapes how the model is constructed and subsequently extrapolated. Disagreement over how a phenomenon progresses over time necessarily results in distinct extrapolation models. Secondly, as an applicable principle for forecasts generally, evaluative measures should be emplaced to assess how effective the methods are for predicting future outcomes.

Seismology offers one last narrative which transitions the conversation on extrapolation models to that of policy implications. In late 2012, six Italian scientists and a government official were convicted in a court of law for manslaughter in the wake of a 2009 earthquake in L’Aquilla, Italy which had resulted in over 300 deaths. The core argument for the prosecution is that the seven defendants failed to provide adequate warning to the people of L’Aquilla and, furthermore, in public statements prior to the earthquake downplayed the possible risk of a future disaster. To some, it appeared as though the government officials provided a deterministic answer by stating there would not be a big earthquake in response to a probabilistic question on the likelihood of occurrence. Critics of the trial conflates the verdict with the conclusion that failed

24 Fountain 2011
predictions are tantamount to criminal activity. Elsewhere, the critics’ conversation has
played out in asking when a forecast is wrong. As will be discussed in the following
section on strategic intelligence, a deterministic extrapolation model is wrong when
present action is no longer explainable by past events. Or, put another way, an
extrapolation model is wrong when it answers the right question by identifying
discontinuity for the phenomenon under observation.

Intelligence

The intelligence field illustrates the policy implications for extrapolation
modeling. Intelligence is information that has been collected, processed, and narrowed to
meet the policymaker’s needs. Policymakers, in turn, use intelligence to take action in
the present so as to shape future events. Currently in its fifth installment, the Global
Trends report provides a prime example for how forecasting and extrapolation are best
used in the service of policy. Published by the National Intelligence Council, the Global
Trends report looks fifteen to twenty years into the future to identify the baseline
trajectories for those trends deemed critical to United States national security interests.
Its most recent publication, Global Trends 2030, identifies four such ‘megatrends’ in
individual empowerment, diffusion of power, demographic patterns and the

25 Diacu 2012
26 Ulfelder 2012
27 Lowenthal 2008, 1
food/water/energy nexus. The baseline trajectories for each of these megatrends are meant to inform, not constrains, the policymaker. If the trajectory for a particular trend outlined in the *Global Trends* report is in accordance with US national interests, policymakers should pursue a course of action that reinforces the driving forces behind this trend. If, however, the trajectory threatens US national interests, policymakers should proceed with a course of action to bolster against the changes implicit in the given trend. After identifying the baseline trajectory, the key question then becomes how to identify when the trend departs from its path. This section will examine the use of indicators and indications in extrapolation models within the Intelligence Community to draw policy implications for how to identify when present action is no longer explainable by past behavior.

Spread across three volumes, Cynthia Grabo wrote the first professional handbook on strategic warning in the midst of the Cold War. Following the September 11th, 2001 terrorist attacks the first two volumes were declassified and released for public dissemination. In the wake of strategic surprise, a high demand was placed on literature that spoke to the possible means by which changes in the operating environment may be identified. Indicators and indications are the mainstay of warning intelligence, a subset of the larger intelligence enterprise concerned with two main functions—the continual monitoring for routine or baseline trajectories and the points of departure that may signal

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28 Burrows 2012, ii

29 Fingar 2011, 57

30 Grabo 2010

31 For further discussion on the role of strategic surprise, see Handel 1984
an exceptional crisis. Here, an indicator is defined as the “known or theoretical step” that a phenomenon may proceed upon that suggests a previously-identified alternate trajectory. An indication is defined as information that verifies any of these steps are being executed. The distinction between indicators and indications is one of “expectation and reality.”

Although Grabo does not explicitly state it in her work, warning intelligence is essentially the construction of a conceptual model as described by Robert Clark in *Intelligence Analysis: A Target-Centric Approach*. The intent of the conceptual model is to forecast when and how a phenomenon under observation may undergo change, along previously assessed courses of action. Seen as such, warning intelligence as a conceptual model is best viewed as an extrapolation based upon the assumption that past behavior is the best predictor of future action. Displaying the baseline trajectory is necessary to establish detectable change in the observed phenomenon, thereby responding to the first flaw described in this paper by identifying discontinuity. As such, the model is not a prediction of what will happen, but a forecast of future action based on the assumption that all key driving forces remain constant without the addition or subtraction of new forces upon the phenomenon. The distinction may be subtle in explanation but is significant in its policy implications. The world is a complex and dynamic system where change is certain. The question then becomes not whether a trend will change, but in what ways the key driving forces will alter a phenomenon’s trajectory.

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32 Ibid., 3

33 Ibid., 10

34 Clark 2004, 30
over time. Taken as such, the departure from the baseline trajectory is a ‘game-changer’ event, the specifics of which may be unknowable but whose occurrence should be continually observed for in accordance with previously established indications.

Conceptually, the term ‘game-changers’ as used in this paper shares a common definition with its usage in the *Global Trends 2030* report. Game-changers are those forces that lead the phenomenon under observation to depart from its established baseline trajectory and to proceed along an alternate course of action. The *Global Trends 2030* report identifies a total of six game-changers that the National Intelligence Council determined will influence how the megatrends proceed over time in shaping future events.\(^{35}\) Each game-changer is presented within a framework of identifying its present state, a narrative describing how the game-changer may depart from the established trajectory, and a plausible future state. Perhaps beyond the scope for the *Global Trends* report series, but a central focus for this paper, is the question of how to identify an impending game-changer. Methodologically, this entails establishing a series of indications to identify points of departure along alternate trajectories. Practically speaking, this process entails conceptualizing what alternate scenarios a given phenomenon may proceed along when exposed to the game-changer’s influencing power.

From a policy standpoint, the question remains as to what course of action to proceed along upon identifying the phenomenon’s changing direction.

One final point on game-changers is that singular departures from the baseline trajectory do not, in of themselves, present an alternate path from which the phenomenon is set to proceed. Instead, the singular data point may be a statistical improbability, or an

\(^{35}\) Burrows 2012, 8
outlier. Recent literature, however, suggests that at least some rare yet large events should actually be considered a probability and not an outlier. Aaron Clauset and Ryan Woodard examine worldwide global terrorism data from 1968 to 2007 and conclude that an event similar in scale to the September 11th, 2001 terrorist attacks had an 11-35% probability in occurring.36 Although the methodological processes by which Clauset and Woodard come to their conclusions relies upon probabilistic modeling, instead of deterministic extrapolations as examined in this paper, the policy implications are applicable, nonetheless. As noted in the previous section on seismology, the model’s construction shapes its outcomes and, by extension, establishes what instances constitute a continuous departure from the baseline trajectory. Identifying game-changers, then, becomes a matter of detecting changes in the established baseline trajectory. Or, put another way, indications for an impending departure from a given phenomenon’s trajectory precede the manifestation of the game-changer. The policy implication is to develop an alternate course of action upon receiving information that the trend is changing, be it to capitalize upon the phenomenon’s new direction or mitigate against the resulting consequence.

36 Clauset and Woodard 2012, 2
CHAPTER THREE: EXPLORING ONE EXTRAPOLATION MODEL

The purpose for this chapter is to review one aggregated extrapolation model present in the conflict prediction literature that will later serve as the basis for a research design proposed and executed in the following chapters.\(^1\) Specifically, this section will illustrate the implications associated with aggregate modeling in exploring the Red Queen Hypothesis as proposed by Neil Johnson. After providing an overview of the Red Queen Hypothesis, this chapter will accomplish three main tasks. First, it will identify the assumptions that must be held true for this particular aggregated extrapolation model to be a valid depiction of the phenomenon it reports to represent. Secondly, the policy-related and theoretical implications brought forth by the Red Queen Hypothesis will be explored. The methodological implications will only be discussed in this chapter as necessary to illustrate the policy-related and theoretical aspects of the Red Queen Hypothesis, leaving a more complete discussion on the methodological components for the following chapter on research design. Thirdly, this chapter will conclude with a critique of this particular aggregated extrapolation model emphasizing where it departs from the scholarly literature.

\(^1\) For further reading on how models are being incorporated into military policy, see “The Science of Civil War: What Makes Heroic Strife” 2012.
The Scale Invariant Nature of Insurgency

On July 13, 2008 an estimated 200 Taliban fighters attacked a remote outpost in Afghanistan guarded by a platoon of soldiers from the 173rd Airborne Brigade Combat Team (BCT) and their Afghan National Army (ANA) counterparts. In what would later be described as the Battle of Wanat, 9 US soldiers lost their lives and a total of 31 were wounded when including ANA counterparts. It was the most significant loss of life in a single battle since the beginning of US combat operations in 2001. Yet, the Battle of Wanat and a roadside bomb that kills a single soldier share common statistical traits that would otherwise be missed were it not for a contemporary understanding of Lewis Fry Richardson’s statistical study of deadly conflict.

In his original study on conflict, Richardson observed smaller incidents of fatal quarrels occurred with greater frequency when compared to large-scale incidents. Homicides occur more often than the wars responsible for much of the world’s casualties. Two key observations made by Richardson in his study are directly applicable to the Red Queen Hypothesis presented here. First, casualties play the central role in determining the magnitude of a fatal quarrel, be it murder or war. Casuality data is also used in the Red Queen Hypothesis to trace a conflict’s trajectory, however, as will be discussed, magnitude is not considered. Secondly, Richardson’s observations present fatal quarrels as following a power law distribution.

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1 The Staff of the US Army Combat Studies Institute 2010
2 Richardson 1948, pp 523, 531
3 Richardson 1960, 4
Dr. Aaron Clauset and others later proved Richardson’s original study to be applicable to terrorist attacks, appropriately coining the phrase ‘Richardson’s Law’ to describe the scale invariant nature for the frequency and severity of terrorist events.\textsuperscript{4} Here, severity is used in the same manner as Richardson originally discussed magnitude. The implication following ‘Richardson’s Law’ is that there exists no statistical difference between large and small terrorist attacks, as “both are consistent with a single underlying distribution.”\textsuperscript{5}

Power law, the statistical engine for Johnson’s Red Queen Hypothesis, has seen wide use for its reported ability to statistically justify a range of phenomenon, from distributions in the frequency of words used in a classic novel to the number of long-distance calls received by AT&T customers in the United States.\textsuperscript{6} Whereas many phenomenon follow a normal distribution, others possess a “heavy tail” and display a “nontrivial amount of weight far from the distribution’s center.”\textsuperscript{7} Here, Figure 3.1 shows a normal distribution for average male and female height. Figure 3.2 shows a power law distribution for US city populations.\textsuperscript{8}

\begin{itemize}
\item \textsuperscript{4} Clauset, Young, and Gleditsch 2007, 58
\item \textsuperscript{5} Ibid.
\item \textsuperscript{6} Clauset, Shalizi, and Newman 2007, 22
\item \textsuperscript{7} Clauset, Young, and Gleditsch 2007, 61
\item \textsuperscript{8} US city population data is also used as an illustrative tool for explaining a power law distribution in Clauset, Shalizi, and Newman 2007.
\end{itemize}
The mean average forms the normal distribution’s center. Male and female heights are usefully illustrated by a normal distribution, such that statements can be made as to how a person’s height compares to the population under observation. As Figure 3.2 demonstrates, US city populations do not follow a normal distribution. Were they to do so, large cities that account for a significant proportion of the US population would fall outside the normal distribution. Instead, US city populations are usefully displayed by a

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10 Clauset, Shalizi, and Newman 2007, 25
power law distribution that accounts for a few events responsible for a nontrivial portion of the phenomenon outside the distribution’s average.\textsuperscript{11} It is important to note that simply observing an apparent power-law distribution is not sufficient for explaining the phenomenon under observation. Instead, these observations must be coupled with a theory responsive to the question regarding what “genuinely new insights” have been achieved.\textsuperscript{12} For Johnson, the Red Queen Hypothesis is offered up as an explanatory panacea to understand the heavy-tailed distribution for hostile attacks by a mechanistic nature of insurgency as outlined in this particular extrapolation model.

With this in mind, Johnson presents his work as an important contribution to the “operationally relevant questions of how the underlying arms race evolves over time, or when fatal attacks might occur.”\textsuperscript{13} Assigning the Red Queen to the niche field of conflict prediction within the broader discipline of forecasting, there remains an understandable appeal in presenting insurgency as a simple, mechanistic model with a unidirectional causal relationship.

**Literature and Biology: Origins of the Red Queen Hypothesis**

With its origins in children’s fiction literature, Leigh Van Valen presented the Red Queen Hypothesis as a new selectionist theory in the field of evolutionary biology. At its core, Van Valen’s proposition is that “what one species gains others lose to the

\textsuperscript{11} Ibid., 1-2

\textsuperscript{12} Stumpf and Porter 2012, 666

\textsuperscript{13} Johnson et al. 2011a, 81
same extent, and vice versa."\textsuperscript{14} The hypothesis’s namesake can be traced back to Lewis Carroll’s \textit{Through the Looking Glass}, where the Red Queen informs Alice that, “It takes all the running you can do, to keep in the same place.”\textsuperscript{15} Similarly, Johnson finds the insurgent (Red Queen) and military/counterterrorism force (Blue King) are defined by a relationship of adaptation and counter-adaptation. The Red Queen Hypothesis serves as the theoretical driver behind Johnson’s observed pattern of escalation in insurgent attacks.\textsuperscript{16} It does so without requiring “knowledge of specific adaptation or counter-adaptation mechanisms,” thus avoiding any dialogue regarding exogenous factors such as insurgent cell size, coalition military tactics and local population sentiments.\textsuperscript{17}

Adjusting the Red Queen Hypothesis to his own ends, Johnson proposes an insurgency’s trajectory is largely driven by the insurgent’s continual striving to kill coalition military forces quickly and successfully. Successful repetition of the task leads to shorter times required for the task’s completion in successive iterations.\textsuperscript{18} In doing so, Johnson demonstrates the possibility to represent the relative advantage or disadvantage insurgents hold to coalition military forces measured by the frequency and escalation of hostile attacks.

\textsuperscript{14} Van Valen 1974, 90

\textsuperscript{15} Carroll 1999

\textsuperscript{16} It should be noted that, although, Johnson presents the Red Queen as a ‘hypothesis’—it may more appropriately be termed ‘theory’ based on its usage. In fact, Johnson refers to the ‘Red Queen Hypothesis’ as a ‘broad-brush theory’ in explaining its universal applicability. Recognizing the Red Queen is, at times, treated as an empirical explanation for an observable phenomenon consistent with what one would find for a ‘theory,’ it is referred to in this paper as a ‘hypothesis’ for matters of consistency.

\textsuperscript{17} Johnson et al. 2011a, 83

\textsuperscript{18} Ibid., 81
Here, a few operational definitions are in order. Hostile attacks are defined as any insurgent activity resulting in at least one coalition military death. Frequency, expressed as $\tau_n$, is measured as the time interval in days between the current and immediately preceding hostile attack. The $\tau_1$ value is the time interval in days between the first two hostile attacks in a given province. Essentially, $\tau_1$ is the starting frequency for an insurgency in a given area. Escalation, expressed as $b$, is the rate at which the time interval between consecutive hostile attacks change over time.\(^{19}\) A negative $b$ value reflects an escalating insurgency characterized by an increasing number of hostile attacks over a set period of time, whereas a positive $b$ value reflects a de-escalating insurgency.\(^{20}\)

The Red Queen as a Model

Expanding upon the Red Queen’s presentation as a model, it is useful to identify both the intended phenomenon under observation and its key driving forces. Here, the key driving forces are identified as the frequency and escalation of hostile attacks. All other forces that may influence the phenomenon over time are explicitly deemed irrelevant and excluded from the modeling. Presented as a “broad-brush theory,” the Red Queen examines the adaptation and counter-adaptation between insurgents and coalition military forces without requiring knowledge as to the specific mechanisms.\(^{21}\) Factors such as insurgent membership, coalition military technology or a local population’s

\(^{19}\) Ibid., 81-82

\(^{20}\) See Appendices A and B for individual province-level power law functions and log-log scatter plots for hostile attacks.

\(^{21}\) Johnson et al. 2011a, 83
“hearts and minds” are presumably captured in the larger dynamic between the frequency and escalation of hostile attacks representative of the insurgency under observation.

If Johnson is correct in his aggregated extrapolation model, the Red Queen is a useful instrument for predicting future fatal days based upon the past behavior of hostile attacks. In fact, the prediction formula for determining a future hostile attack in a given province need only require the time interval between the first two events. The policy implications are such that decision-makers could be provided with meaningful estimates as to an insurgency’s progression across a theater of operations, categorized down to the provincial level. Forecasting an insurgency’s trajectory across time for a set of given provinces would be instrumental in allocating manpower and resources to alter or reinforce the projected outcome. From a methodological standpoint, the Red Queen distills the complex nature of insurgency down to two key driving forces—the frequency and escalation of hostile attacks. The theoretical implications for the Red Queen fall in line with the observations that can be made for any aggregated extrapolation—namely, its imperviousness to ‘game changers’. At its core, the Red Queen operates on the assumption that past behavior is the best predictor of future action. It is why, methodologically, Johnson can make claim at predicting future attacks based solely upon the time interval between the first two attacks. In doing so, however, a key vulnerability to the Red Queen’s logic is revealed. Not only is insurgency scale invariant, but in order

22 Johnson et al. 2011b, 5

23 Here, it may be useful to recall Thomas Fingar’s observations on the *Global Trends* reports discussed in Chapter 2. An insurgency’s trajectory, like the trends identified in the *Global Trends* reports, provides policy-makers an opportunity either reinforce key drivers or mitigated against impending change in accordance with their overall objectives. See Finger 2011, 57.
for the Red Queen to remain a valid model, insurgency must also be temporally invariant as well.

**A Critical Look at the Red Queen Model**

Critiquing the Red Queen, as the concluding section for this chapter, helpfully begins with exploring further its theoretical implications. The dynamic relationship of adaptation and counter-adaptation between insurgent and coalition military force is not only captured by two key driving forces, but at a singular moment in time to be projected across the insurgency’s existence. Although the dataset is categorized down to province-level, and even available for further refinement by specific mode of weapon system used, all hostile attacks are examined across a single time series. Hostile attacks are effectively aggregated across the temporal dimension to present a single snapshot of an insurgency. Its methodological design prohibits its generalized theoretical claims of a “broad-brush” approach to capture the adaptation and counter-adaptation between two opposing forces.

To illustrate this point further, Figure 3.3 is included below from the original study, graphically displaying the relationship between $\tau_1$ and $b$ for individual Afghanistan provinces along a best linear fit (see Figure 3.3, Box C).
As presented, Figure 3.3 Box C appears to demonstrate that the frequency ($\tau$) and escalation ($b$) of hostile attacks across 14 Afghan provinces from 2001 to 2010 occurred along a trajectory best described by a power law function. Instead, what Box C actually displays is a generalized relationship formed from aggregating province-level data to a single timeframe spanning the better part of ten years. The original study is an aggregated extrapolation model based upon historic attack data that is only able to forecast future events insofar as their continuance along a previously established baseline trajectory, defined in this case by a power law function. It fails to account for changes in the observed phenomenon, hostile attacks perpetrated by an insurgent force against coalition military, and strongly suggests the presence of unaccounted driving forces beyond the frequency and escalation rates identified in the original study.

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24 Johnson et al. 2011a, 82
From a policy standpoint, what the Red Queen may actually provide for the decision-maker is not a prediction for the next attack, but rather a baseline trajectory for how an insurgency may play out barring any “significant structural changes.” Although not clearly stated by Johnson in his published work on the subject, the adaptation and counter-adaptation between insurgent and coalition military force is not captured by the model itself, but rather by comparing actual attacks against the predicted baseline trajectory. Taken as such, the Red Queen becomes less an instrument for predicting the next attack, and more of an assessment tool for determining whether the Blue King is effectively adapting to Red Queen behavior.

One final policy-related critique is that severity, measured by the total number of casualties attributed to a single hostile attack, is deliberately excluded as a key driving force for the extrapolation modeling offered by the Red Queen Hypothesis. In response, Johnson would likely argue that the scale invariant nature between frequency and escalation of hostile attacks makes severity an irrelevant factor in determining the insurgency’s trajectory. From a policy standpoint, however, the severity of hostile attacks in a given province is instrumental in both the military and political decision-making process. Province A may experience more catastrophic attacks, instances whereby multiple casualties are attributed to a single enemy event, and ultimately experience a greater loss of coalition military death than Province B. Province B, however, may have more hostile attacks overall. The Red Queen Hypothesis would, in

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25 Johnson et al. 2011b, 7

26 Clauset, Young, and Gleditsch 2007, 59-60 also point to the importance in studying attack severity when examining terrorist events.
this case, forecast a trajectory that leads decision-makers to believe insurgency is progressing at a faster rate in Province B than Province A. Or, put another way, even though the Red Queen Hypothesis observes the Iraq Insurgency at the province-level, it fails to account for sub-national variance when examining the process by which the phenomenon changes over time.\textsuperscript{27} Important to note is that the manner in which insurgency is represented in by the Red Queen Hypothesis, Province B would indeed be escalating at a faster rate than Province A. Equally important is that were the decision-maker to rely on the Red Queen Hypothesis, they would do so with only partial knowledge of the phenomenon, consequently failing to address the higher casualty rates present in Province A.

Table 3.1 is included below to demonstrate the implications in removing severity from the model. It includes the total number of hostile attacks and those attributed to IEDs, both unfiltered and filtered for the 1-day data resolution constraint:

<table>
<thead>
<tr>
<th>Province</th>
<th>IED (filtered)</th>
<th>IED (Unfiltered)</th>
<th>ALL (Filtered)</th>
<th>ALL (Unfiltered)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Al Anbar</td>
<td>222</td>
<td>402</td>
<td>561</td>
<td>1144</td>
</tr>
<tr>
<td>Al Tammim</td>
<td>25</td>
<td>44</td>
<td>43</td>
<td>70</td>
</tr>
<tr>
<td>Babil</td>
<td>57</td>
<td>96</td>
<td>103</td>
<td>178</td>
</tr>
<tr>
<td>Baghdad</td>
<td>445</td>
<td>778</td>
<td>653</td>
<td>1178</td>
</tr>
<tr>
<td>Basra</td>
<td>34</td>
<td>49</td>
<td>74</td>
<td>112</td>
</tr>
<tr>
<td>Diyala</td>
<td>78</td>
<td>133</td>
<td>127</td>
<td>216</td>
</tr>
<tr>
<td>Ninawa</td>
<td>54</td>
<td>77</td>
<td>129</td>
<td>204</td>
</tr>
<tr>
<td>Qadisiyah</td>
<td>15</td>
<td>17</td>
<td>24</td>
<td>28</td>
</tr>
<tr>
<td>Salah Din</td>
<td>127</td>
<td>178</td>
<td>222</td>
<td>319</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1057</strong></td>
<td><strong>1774</strong></td>
<td><strong>1936</strong></td>
<td><strong>3447</strong></td>
</tr>
</tbody>
</table>

\textsuperscript{27} See Shapiro, Fair, and Rais 2011 for further research regarding terrorism and political violence in Pakistan and how the phenomenon of sub-national variance is being studied in the field.
Interpreting this data to account for severity can be accomplished by considering the ‘filtered’ quantity to be the total number of days in which a hostile attack occurred, and the ‘unfiltered’ quantity as the total number of coalition military forces killed. It is only in observing the data in this disaggregated form that it becomes apparent that IED attacks in Al Anbar Province were more severe than in any other province, measured as the total number of IED casualties across the total number of fatal days.

Johnson acknowledges the data resolution time scale of 1 day in the original research design, identifying no consequences to the study’s overall conclusions. Consequently, hostile attacks that occur within an individual Iraqi province on the same calendar day are aggregated in the model such that no more than one hostile attack is accounted for on a given day.

The constraints imposed by day-level temporal resolution appear to be a common challenge for the study of terrorism. Aaron Clauset and Kristian Gleditsch are faced with similar timing resolution constraints in their study of statistical patterns found in the frequency and severity of terrorist attacks over time. Identifying a resulting inverse frequency from the 1-day temporal resolution, Clauset and Gleditsch aggregate attacks perpetrated by a single group to construct a severity equivalent to all individual attributable attacks that occurred on a given day. What separates Johnson’s research from that of Clauset and Gleditsch is that the latter recognize and attempt to account for the impact of 1-day temporal resolution. It should be noted that the two papers are examining similar but distinct phenomenon; however, the constraints imposed by the data

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28 Johnson et al. 2011a, 81
29 Clauset and Gleditsch 2012, 6
resolution can reasonably be expected to impact the results from both studies. For purposes of comparing results with Johnson’s original study, the research design proposed and executed here does not account for the 1-day data resolution constraints imposed upon it. Future research, however, would benefit from acknowledging and accounting for the likely impact a 1-day temporal resolution has upon the study’s results.\textsuperscript{30}

Divergence between the scholarly literature and the Red Queen

Having presented Johnson’s framework for the Red Queen Hypothesis examined in this paper, it is necessary to highlight where his explanation diverges from the existing literature on insurgency and state–non-state actor dynamics. Models are meant to be useful representations of reality. The Red Queen Hypothesis, however, possesses three main lines of departure from the scholarly work on insurgency that consequently distorts its own purported representation. Conceivably, these departures from the literature would be operationally irrelevant were the Red Queen Hypothesis to accurately forecast future hostile attacks. A central premise for this paper, however, is that the original study fails due to two inherent flaws in aggregated extrapolation models. The alternate study described in the following chapters demonstrates how introducing distinct breakpoints leads to findings that would be otherwise masked when the entire phenomenon is viewed in aggregate.

Here, the Red Queen Hypothesis’s departure from the scholarly literature is presented for two reasons. The alternate study, using the same dataset as the original

\textsuperscript{30} Thanks to Dr. Aaron Clauset for discussing 1-day data resolution constraints with the author, May 2012.
study, necessarily incorporates the same divergences from the literature. Acknowledging where the study diverges from the scholarly literature contextualizes the subsequent findings and informs the reader on how these decisions in construction shape and constrain the policy implications.

The first divergence from the literature is that the Red Queen Hypothesis fails to account for any role the local population may play in an insurgency campaign. Broadly speaking, there are two competing paradigms for how to execute a counterinsurgency. Both, however, rely upon the local population. Enemy-centric counterinsurgency, at its core, proceeds with the assumption that “war is war” and the purpose of war is to defeat the enemy force. Critics would point to the American experience in Vietnam with its emphasis on attrition as a blunt example of an enemy-centric counterinsurgency strategy. There is a contemporary and more nuanced repackaging of this strategy to be found in the targeted killing campaign currently being executed by the Obama Administration through the use of special operations and unmanned drone strikes. Even this strategy, however, uses human intelligence (HUMINT) collected from the local population in order to prosecute its mission to disrupt the enemy network’s ability to effectively operate. In an enemy-centric counterinsurgency paradigm, the local population is still a necessary stakeholder that influences the dynamic between insurgent and counterinsurgent.

31 Nagl 2005, 27
32 There is a related argument that the lethal targeting cycle, left unchecked, reinforces the key drivers responsible for the ‘next attack’—ensuring that past behavior of terrorist attacks and counterterrorist responses becomes the best predictor for future such interactions. For further reading on this subject in examining Israeli counterterrorism policies, see Byman 2011, 361
33 Lamb and Munsing 2011, 7
Population-centric counterinsurgency is the other campaign paradigm, and as the name suggests, places the local population at the center of its strategy. Presented through the lens of conventional military doctrinal terms, David Kilcullen relays the oft-cited dilemma facing a counterinsurgent force tasked with killing the enemy. Enemy forces must be ‘fixed,’ or prevented from moving for a specified period of time, before they can be effectively destroyed. Completing this task is problematic when faced with an opposing force that is not tied to physical terrain like a conventional army. Instead, so the population-centric strategy offers, the counterinsurgent must ‘fix’ the insurgent force by separating them from the local population. It is, as Mao Tse-Tung observed, to ‘separate fish from water.’ Separating the insurgent from the local population narrowly focuses on the insurgency’s necessity to garner its support for political power, which broadly speaking, remains the insurgent’s goal. Whereas the enemy-centric approach may be seen as a mostly military endeavor, a population-centric approach emphasizes the primacy of civilian power.

Taken to its extreme interpretation, Johnson’s presentation is a refutation of population-centric counterinsurgency strategy. It is to say that winning hearts and minds is irrelevant to the outcome of an insurgency campaign, instead focusing solely on the insurgent-coalition military dynamic as measured by the frequency and escalation of hostile attacks. In a September 2011 working paper, Johnson discussed the interrelated

34 Kilcullen 2010, 9
35 Nagl 2005, 28
36 Galula 2006, 4
37 Galula 2006, 56, 53
dynamic between insurgents (Red Queen), coalition military forces (Blue King) and the local population (Green). Yet, neither the relationship between $\tau_1$ and $b$ nor the mathematical expression Johnson provides for the Red Queen Hypothesis incorporate the local population. Johnson justifies this decision by arguing the local population can be expressed as a passive background that receives the impact of hostile attacks but does not actively influence either of the other parties. This is however an unconvincing position when the only variable observed is hostile attacks measured by coalition military fatalities. Only concerned about the frequency and escalation of hostile attacks measured by coalition military casualties, the Red Queen Hypothesis appears to be more closely representing an enemy-centric counterinsurgency strategy. As such, the Red Queen Hypothesis may capture certain aspects pertaining to how insurgents and military forces interact, but does so at a sacrifice. Insurgency is a multistakeholder endeavor between the insurgent, local population, host-nation security force, and coalition military in cases where an external intervention occurs. The Red Queen Hypothesis, however, reduces insurgency to a bilateral affair between two opposing sides.

In this vein, the second main line of departure identified here is the failure to address more than two parties engaged in a particular conflict. This is of particular concern when examining instances whereby external intervention is critical to the counterinsurgency campaign under observation. Host-nation security forces play a vital role as both a force multiplier and long-term solution in a campaign largely led by a

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38 Johnson 2011, 20

39 Ibid., 33

40 See Kilcullen 2010 and Ucko 2009
multinational consortium of military forces.\textsuperscript{41} The Red Queen Hypothesis, however, is only capable of accounting for a dynamic relationship between a monolithic insurgent force and a single opposing military. This is particularly problematic when examining counterinsurgency campaigns in Iraq and Afghanistan, where insurgents intents on degrading the perceived legitimacy of the national government view host-nation security forces as the preferred target for attack.\textsuperscript{42} Furthermore, host-nation security forces possess inferior military capabilities in comparison to the external coalition military intervention force, presenting them as the more desirable target for attack. It is possible that the absence of both local population and host-nation security forces from the Red Queen Hypothesis may be due to a lack of available datasets. Removing them from the model, however, should be done with a caveat that informs the readership as to what constrained findings they may take from the study. Instead, the Red Queen is presented as a “broad-brush theory” that sufficiently captures all critical components for an insurgency campaign.\textsuperscript{43} It is in this regard that the scholarly literature disagrees.

Thirdly, the organizational group dynamics presented in the Red Queen Hypothesis fail to address the scholarly literature on government actors and dissidents. The Red Queen Hypothesis presupposes a singular action between the coalition military forces and insurgent. The broader literature on government and dissident forces, however, looks at conflict and cooperation dynamics so as to capture changes in behavior over time. Here, Stephen Shellman’s work captures the scholarly literature on

\textsuperscript{41} FM 3-24 2009, 8-1

\textsuperscript{42} “Taliban Kill 1,100 Members of Afghan Security Forces in Six Months” 2013

\textsuperscript{43} Johnson et al. 2011a, 83
government and dissident behavior using a similar logical framework as is done in this paper. Shellman examines sequential processes for conflict and cooperation between government and dissident forces over time by disaggregating event data. In doing so, he explores how “government behavior influences dissident behavior and how dissident behavior influences government behavior” in the decisions made by each respective party regarding whether to proceed with conflict and cooperation at a given point in time.\(^{44}\)

Additionally, the Red Queen falls victim to the notion of false borders. The phenomenon under observation is insurgency, geographically bounded along provincial lines. Hostile attacks are categorized at the provincial level, presupposing that the insurgency under observation is similarly constrained by the same borders. In reality, insurgent forces are less constrained by lines on a map that symbolize political boundaries and are, instead, restricted by geographic terrain features.\(^{45}\)

An examination of Shellman’s work provides two distinct divergences from the Red Queen Hypothesis and the study proposed in the following chapter. First, Shellman’s work reflects the scholarly literature’s concern with a range of activities with which government and dissident forces may proceed. Violent and non-violent conflict or cooperation are examined as choices that a government or dissident may proceed with at a given decision point.\(^{46}\) This government – dissident dynamic is absent both in the Red Queen Hypothesis and in the alternate study proposed in the following chapter. In part,

\(^{44}\) Shellman 2006, 570

\(^{45}\) For further discussion on insurgency and the notion of false borders, see Galula 2006 and Salehyan 2011.

\(^{46}\) For further discussion on a sequential testing of competing theories regarding repression and violence in government–dissident behavior, see Moore 1998
this is because the insurgency campaign modeled in the Red Queen Hypothesis operates under the assumption that insurgents will continue to attack coalition military forces as quickly and effectively as possible. Consequently, any measured changes in the frequency and escalation of hostile attacks does not provide an alternate behavior with which the coalition military force or insurgents may be proceeding. Or, put another way, a measured decline in hostile attacks in the Red Queen Hypothesis does not suggest the insurgents have chosen to engage in cooperative measures with the coalition military forces.

Secondly, Shellman’s primary work on government and dissident dynamics disaggregates event data, whereas the study proposed here proceeds with temporal disaggregation. In doing so, Shellman is capable of examining “the sequences of interaction that escalate conflict and sequences of events that de-escalate conflict and give rise to cooperation.” Disaggregating event data becomes necessary in order for Shellman to accomplish the first task—examining the process by which government and dissident forces influence each other’s behavior along a conflict-cooperation dynamic.

This last point highlights the shared logic with which both Shellman’s work on government-dissident behavior and this paper proceed. Aggregation, be it temporally or event-based, masks the very nuances which may indicate in what direction a phenomenon’s trajectory is likely to travel. Elsewhere, Shellman examines the biases generated by temporally aggregating event data. Rightfully, Shellman’s concern is that little attention is paid as to how temporal aggregation biases the inferences drawn from

47 Johnson et al. 2006, 13

48 Shellman 2006, 565
those studies. It is important to note that here, still, Shellman is interested in the conflict-cooperation dynamics between government and dissident forces. Regardless, temporal aggregation should occur at an appropriate level for the phenomenon under observation. The difficulty, Shellman notes, is that conflict between government and dissident does not occur along an “‘appropriate’ (i.e., natural) unit of time.” Consequently, Shellman concludes that it is necessary to test the sensitivity for a study’s results “across various time intervals when assessing the tenability of knowledge claims.” Studies with results that “hold across multiple levels of aggregation” should be given greater weight.

Implications

The most significant concern for the original study remains the two flaws inherent to extrapolation models. The Red Queen Hypothesis is an aggregated extrapolation model that operates on the assumption that past behavior is the best predictor for future action, incapable of identifying discontinuity with the baseline trajectory when using its original construct. Consequently, changes in how the insurgency escalates over time are masked by aggregation. It is important to reiterate that the three main departures from the literature are included here to inform the reader as to how the policy implications from the Red Queen Hypothesis and, by extension, the alternate study are constrained by these omissions. Or, put another way, were the original study not inhibited by the two inherent flaws for aggregated extrapolation models, it would still fail to accomplish its stated goal. For example, when examining the Iraq Insurgency, the original study’s claim

49 Shellman 2004, 103

50 Ibid., 103
at predicting the next hostile attack would require a caveat. The Red Queen Hypothesis would not predict the next hostile attack conducted by insurgents, but rather, the next hostile attack targeting coalition military forces. Attacks against host-nation security forces are unaccounted for, a limitation acknowledged to be present in the alternate study as well.
CHAPTER FOUR: METHODOLOGY

Ultimately, this paper rejects the major findings offered by the Red Queen Hypothesis and proceeds with an alternate study. Using the same model and data described in the previous chapter, Chapter 4 begins with a novel research design for exploring how to recognize impending ‘game changers.’ In doing so, it also explores whether escalatory campaigns, such as an insurgent-coalition military arms race, are explainable by a power law function. Introducing distinct breakpoints demonstrates the influence temporal aggregation has upon the original study’s results. Temporally disaggregating the original dataset shows that the frequency and escalation of hostile attacks follow a trajectory that extends along a power law function for only indeterminate periods of time. This is to say that power law functions provide an acceptable goodness-of-fit for hostile attacks up until a point in time where they no longer do so. It is this inconsistency that brings the entirety of the explanatory power offered by the Red Queen Hypothesis into question. Instead, the study proposed and executed here provides not only a critical methodological response to the Red Queen Hypothesis, but provides the foundations for an alternative conversation on extrapolation models. The results from the study presented in this paper demonstrate that introducing distinct breakpoints to disaggregate an extrapolated trajectory reveals certain nuances that would otherwise be masked and, effectively, leads to alternative findings.
Disaggregating Time: Introducing Distinct Breakpoints to the Baseline Trajectory

Using the original study’s dataset for IED attacks in individual Iraqi provinces between 2003 and 2010, the study proposed and executed here introduces distinct breakpoints to observe how disaggregation influences the model’s representation for insurgency. These breakpoints can be grouped into two categories, indications-driven and event-date breakpoints. Indications-driven breakpoints are established based upon an observable change in the phenomenon’s behavior, while an event-based breakpoint is established at a given point in time deemed significant and relevant to the phenomenon.

Here, it is important to note two points regarding the decision to use the Iraq dataset. First, the conclusion of Operation Iraqi Freedom (OIF) presents a complete dataset for interpretation spanning a significant portion of the conflict from the 2003 invasion to the 2010 drawdown.\(^1\) Whereas combat operations in Afghanistan remaining ongoing as of this paper’s writing, using the Iraq dataset allows for observations to be made regarding the conflict’s trajectory in its entirety.\(^2\) To avoid a selection bias, Phase 1 and Phase 2 testing are also conducted for all hostile attacks in the same nine Iraqi provinces to ensure results are not limited to a specific mode of attack—even one

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\(^1\) Operation Iraqi Freedom concluded in August 2010 with the US troop level reduction to 50,000. The continued US Military presence beyond August 2010 falls under Operation New Dawn. See Jaffe, 2010.

\(^2\) Although Johnson describes the dataset for the original study to range from 2003 to the 2010 drawdown, the terminating datapoints for the Iraqi provinces under observation are dated late 2009 through early 2010. There are, consequently, hostile attacks which occurred in the final months of Operation Iraqi Freedom which are neither included in the original study or the one proposed and executed in this paper. The number of hostile attacks excluded are small enough it is not believed to have any meaningful impact on results.
responsible for the most US casualties.\textsuperscript{3} Secondly, Johnson identifies the Iraq Insurgency as the only campaign observed in his study that includes both escalatory and de-escalatory components.\textsuperscript{4} Consequently, as will be explained below, the original study contains an indications-driven breakpoint where Johnson identifies the insurgency to be de-escalatory and will form the basis for Phase 1 in the study proposed here.

Only concerned with the escalatory phase of the insurgency, Johnson calculates a cumulative moving average (CMA) for $\tau$ values between each hostile attack in a given province. Identifying the “minimum value attained by the cumulative moving average (CMA) of tau,” Johnson establishes this as the endpoint for his study, effectively censoring the data at the point in which subsequent CMA values increase over time.\textsuperscript{5} The power law functions for each individual Iraqi province are only calculated from $\tau_1$ to this defined minimum value, effectively capturing the pre-$n$ shift moment. Collectively, these indications-driven breakpoints span an approximate 33-month period ranging from May 2005 to February 2008.\textsuperscript{6}

In the original study, Johnson states that the power law function provides up to a 70% improvement over an exponential fit for three-quarters of all provinces under

\textsuperscript{3} While IEDs caused more US casualties than any other mode of attack in Iraq, bullets proved to be the most lethal. Here, lethality was determined by calculating the percentage of casualties when compared to the total number of instances, accounting for those wounded in action. See “More Attacks, Mounting Casualties” 2007 and “Why do Bullets Kill More Soldiers in Iraq?” 2012.

\textsuperscript{4} Johnson et al. 2011a, 82

\textsuperscript{5} Ibid. Supported Online Material (SOM) Methodologies Section

\textsuperscript{6} Ibid. Supported Online Material (SOM) “pre_nshift_decurves.ods”
observation.⁷ Although this observation was made in direct reference to provinces in Afghanistan, the methodological steps are repeated in this alternate study for the Iraq Insurgency on the basis that the central premise should hold true. If the Red Queen Hypothesis is to remain valid, a power law function should perform better than an exponential fit for all time series presented in this alternate study. Otherwise, a power law function is no longer a sufficient explanation for the frequency and escalation of hostile attacks over time.

The research design in this paper applies a common methodology across two empirical testing phases. For both phases in this paper’s study, a total of 1057 unique IED hostile attacks spanning nine provinces are examined across the two time series under observation—referenced as T1 and T2 for Phase 1, T1_pre-2007 and T2_post-2007 for Phase 2. Each time series is, in effect, separated by a distinct breakpoint introduced to test the effects of temporal disaggregation for the entire phenomenon under observation—in this case, the Iraq Insurgency from 2003 to 2010. Power law functions and exponential fits are calculated for each designated time series in the Iraq IED dataset separated by distinct breakpoints. The resulting pearson r-squared value is then compared against an r-squared value for an exponential fit applied to the same province. The equation used is: \((r^2_{\text{PLF}} - r^2_{\text{exponential}})\times100\). Instances where the exponential fit outperforms the power law function use the following equation, so as to keep all results positive: \((r^2_{\text{exponential}} - r^2_{\text{PLF}})\times100\).⁸

⁷ Johnson et al. 2011a, 81

⁸ See Appendices A and B for individual province-level calculations across both Phase 1 and Phase 2 observations.
If the original study’s observations are to be valid, the most immediate policy implication is that the Iraq War is the only counterinsurgency to be effectively won where winning is defined as slowing down the rate of hostile attacks. This is significant in that the original study included data for the war in Afghanistan, Hezbollah, and other global terrorist attacks. Here, escalation and de-escalation refer to the rate at which the average frequency (τ) changes over time. This subject will be engaged in more detail in Chapter 5 where the results from the alternative study are presented. For now, it is only necessary to consider that there may be escalatory and de-escalatory components in other insurgency campaigns that are masked by the aggregated extrapolation modeling. Identifying these nuances in the conflict’s trajectory can provide meaningful alternative understandings for the campaign.

Phases and Time Series Explained

In Phase 1, the power law function for the post-\(n\) shift moment is calculated for purposes of comparison. The Iraq dataset, bifurcated by the CMA minimum value, presents two distinct time series for evaluation. Only one, however, is observed in the July 2011 *Science* article as Johnson cites his study to be solely interested in escalation. Consequently, \(\tau\) calculations and \(b\) values for T1 are included as part of the ‘pre-\(n\) shift’

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9 As previously noted, datasets for the wars in Iraq and Afghanistan were obtained from casualty listings provided by [www.icasualty.org](http://www.icasualty.org). All other terrorism datasets were obtained from the Chicago Project on Security and Terrorism (CPOST) and the Memorial Institute for the Prevention of Terrorism (MIPT). A full listing of datasets employed by Johnson in the original study can be found in the Supported Online Material (SOM).

10 An example for insurgencies that possess de-escalatory and escalatory segments is explored further in Chapter 6, specifically looking at Zabul Province in Afghanistan.

11 Johnson et al. 2011a, 82
dataset found in the supported online material. This paper’s research design presents this pre-$n$ shift moment, defined as $T_1$, and compares power law functions for the post-$n$ shift moment, defined as $T_2$. Or, put another way, Phase 1 consists of introducing the indications-driven breakpoint established at the minimum value attained by the cumulative moving average into the entire dataset for the Iraq Insurgency.

Phase 2 in the research design separates the Iraq IED event dataset into two distinct time-series using 1 January 2007 as an event-date breakpoint. The 2007 decision to ‘surge’ five additional brigade combat teams to Iraq while extending those units already deployed in theater is cited as a key policy decision responsible for quelling the escalatory violence that had come to characterize the conflict. Conceivably, a conflict’s trajectory will change direction over time, perhaps multiple times and in significant ways. Establishing the 2007 troop increase as the Phase 2 breakpoint is useful, even though the overall study is not concerned with providing an explanatory narrative for the causal origins to any changes in the phenomenon’s trajectory. If any changes in the insurgency’s trajectory were to be masked by a temporal aggregation for the entire phenomenon, establishing a breakpoint on 1 January 2007 provides a strong opportunity for the nuances to be made apparent. Consequently, an event-date breakpoint is established at 1 January 2007 to separate the Iraq data into pre-surge and post-surge hostile attacks, defined here as $T_{1\text{pre-2007}}$ and $T_{2\text{post-2007}}$. Power law functions and exponential fits are calculated for both time-series and Pearson r-squared values are then compared.

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12 See Bush 2007 and Kagan 2009
The \( \tau \) values for the filtered Iraq dataset are calculated by determining the number of calendar days between a hostile event and the next subsequent attack. For instance, calculating the \( \tau_n \) value for the casualty-producing IED attack that occurred on 31 January 2004 in At-Tamim province requires identifying the next subsequent attack—in this case, 4 April 2004. The number of calendar days between these two successive attacks is 64 and, therefore, the \( \tau_n \) value for the 31 January 2004 IED event is 64.\(^{13}\) Whereas \( \tau_n \) is the “interval between the \((n-1)\)’th and \(n\)’th fatal day, \( \tau_1 \) is the “time interval between the first 2 days with coalition military fatalities.”\(^{14}\) The \( \tau_n \) values for each individual Iraqi province were plotted on a log-log axis.\(^{15}\) The \( b \) value for the time period under observation in each Iraqi province was derived from the power law function, \( \tau_n = \tau_1 n^{-b} \). The introduction of distinct breakpoints establishes a new \( \tau_1 \) value for each time series under observation and effectively alters the resulting trajectory in a non-systematic manner, bringing into question the overall implications originally proposed for the Red Queen.

Were a province’s first casualty to be erroneously labeled as a hostile attack, it would be to effectively introduce an arbitrary breakpoint, altering the phenomenon’s trajectory. The consequences for such an error are observable in the original study when examining Kandahar Province, Afghanistan. The first hostile attack reported in Kandahar is dated 15 April 2002 and identified as an IED attack. A review of the obituaries for the

\(^{13}\) Johnson et al. 2011a, Supported Online Material (SOM)

\(^{14}\) Ibid. 81

\(^{15}\) See Appendices A and B for individual province-level log-log scatter plot graphs.
four service members killed on this date reveals the cause of death to be the mishandling of unexploded ordinance.\textsuperscript{16} This is important in that the 15 April 2002 event does not meet the operational definition for a hostile attack, since the event was not attributed to enemy action. A review of the IED attacks in Kandahar Province which accounts for the need to adjust the $\tau_1$ value from ‘1132’ to ‘89’ (the next hostile attack reported in Kandahar Province is dated 21 May 2005) results in an 11\% reduction in the overall power-law progress-curve improvement over an exponential fit.\textsuperscript{17} While a small number of coalition military casualties may erroneously be attributed to enemy action, there is no indication of a selection bias in this error and the numbers are likely low enough that the study’s overall implications are not impacted—barring one exception. The $\tau_1$ value is critical in establishing the Red Queen’s baseline trajectory for a province’s insurgency. As a matter of due diligence, all entries for the nine Iraqi Provinces used in this study were vetted using obituaries in order to verify the cause of death was attributed to enemy action.

**Summary**

The methodology for calculating the power law function, exponential fit and comparing the pearson r-squared values remains constant across both testing phases. The resulting 1057 hostile attacks spanning nine provinces are examined across both phases in this study. Separately, Phase 1 and Phase 2 testing was conducted for the same nine provinces using all 1936 hostile attacks reported during the observation time to ensure

\textsuperscript{16} “Arlington National Cemetery” 2012

\textsuperscript{17} Johnson et al. 2011a, Supported Online Material (SOM)
results were robust. The empirical testing addresses the decontextualized approach in methods and theory with which Johnson proceeded in his original study. It does so by introducing distinct temporal contexts that allow for opportunities with which exogenous factors, masked in the original study, may influence the relationship between frequency and escalation. Based upon the study design, the $\tau_1$ value can be expected to change at the breakpoint, reflecting a ‘resetting’ of the power-law function. Instances where the exponential fit is shown to outperform the power law function, however, may be indicative of exogenous factors influencing the relationship between frequency and escalation. Such results would question the validity in the explanatory value provided by the Red Queen Hypothesis, effectively demonstrating how temporally disaggregating the original dataset along distinct breakpoints influences the trajectory’s outcome. This study, as noted in the introduction, would not provide a narrative for the causal origins to these changes. It would, however, provide the opportunity to identify nuances in the phenomenon that may be indicative of impending ‘game changers’ using an extrapolation model.

Table 4.1 is included to highlight the distinct methodological differences between the Red Queen Hypothesis and the alternative study described here:

<table>
<thead>
<tr>
<th>TABLE 4.1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Red Queen Hypothesis</strong></td>
</tr>
<tr>
<td>Temporally Aggregated from 2003 to</td>
</tr>
<tr>
<td>the minimum value obtained by the CMA</td>
</tr>
<tr>
<td>Only examines the escalatory portion</td>
</tr>
<tr>
<td>of the campaign, or the pre-$n$ shift</td>
</tr>
<tr>
<td>moment</td>
</tr>
<tr>
<td><strong>Alternative Approach</strong></td>
</tr>
<tr>
<td>Temporally disaggregated across two</td>
</tr>
<tr>
<td>distinct breakpoints, both the CMA and</td>
</tr>
<tr>
<td>1 January 2007</td>
</tr>
<tr>
<td>Examines both escalatory and de-</td>
</tr>
<tr>
<td>escalatory portions of the campaign</td>
</tr>
</tbody>
</table>
**TABLE 4.1 (Continued)**

<table>
<thead>
<tr>
<th>Red Queen Hypothesis</th>
<th>Alternative Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extrapolates an insurgency’s trajectory using the $\tau_1$ value</td>
<td>Resets the $\tau_1$ value at each distinct breakpoint, effectively resetting the insurgency’s extrapolated trajectory</td>
</tr>
<tr>
<td>Focuses on continuity in the baseline trajectory and masks indications for impending ‘game changer’ events</td>
<td>Highlights discontinuity in the baseline trajectory and provides opportunity to measure indications for impending ‘game changer’ events</td>
</tr>
</tbody>
</table>
CHAPTER FIVE: DISCUSSION

If Johnson was correct in his theoretical explanation and methodological testing for the Red Queen Hypothesis, then one could expect three main findings. First, one would expect results consistent with the original study that found a power law function to be a better fit for hostile attacks across provinces under observation. As will be discussed in this section, a power law function provided a better fit for hostile attacks in only five out of nine provinces during the escalatory phase. Secondly, one would expect a power law function to provide a better fit during the de-escalatory phase once the algorithm was reset for the hostile attack immediately following the minimum value attained by the cumulative moving average. Instead, results demonstrate that an exponential line provides a consistently better fit during time-series 2 testing.  

Thirdly, one would expect to find a scale invariant quality when comparing escalatory segments of the insurgency across weapon systems.

Results from this paper’s study do strongly point to three main findings. It is only the last point, however, regarding the scale invariant quality for hostile attacks that is in agreement with the results from the study conducted in this paper. In short, examining the entire phenomenon as done here, challenges the findings offered in the original study.

1 See Appendix C for cross-tabulations for individual province-level performance by phase and time-series regarding power law function and exponential fit.

2 During this study, the IED was examined as a single weapon system and compared to an aggregate for all hostile attacks.
First, insurgencies behave differently during periods of escalation and de-escalation. The results show the power law function is a marginally better explanation during the escalation phase, while the exponential fit is overwhelmingly better during the de-escalatory phase. These observations strongly suggest that the Iraq insurgency’s de-escalation is not strictly the reversal of the escalatory segment. Were this to be the case, it would be expected that the power law function would provide a consistently better fit during both escalatory and de-escalatory segments of the insurgency. The second finding is that not all insurgencies behave the same. Three provinces are consistently better explained by an exponential fit during the escalatory segment of the insurgency across all phases of observation when examining IED attacks. Similarly, four other provinces are consistently explained by a power law function during the escalatory segment of the insurgency across all phases of observation when examining IED attacks. These results imply that not all insurgencies escalate according to a single process, but rather, display sub-national variance across provinces. Thirdly, there is a scale invariant quality to the escalation segment for an insurgency that remains independent of weapon systems employed for the hostile attacks. It is this last point, and this one alone, which is in agreement with the findings from the original study.

In addition, these findings warrant further research as to whether event-date breakpoints may serve as an adequate substitute for indications-driven breakpoints. This

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3 The three provinces which are consistently better explained by an exponential fit during the escalatory segment across all phases of observation when examining IED attacks are: Baghdad, Basra and At-Tamim. The four provinces which are consistently explained by a power law function during the escalatory segment of the insurgency across all phases of observation when examining IED attacks are: Al Anbar, Ninawa, Qadisiyah and Salah Ad Din. It should be noted that this pattern also holds when examining all hostile attacks for Phase 1. See Appendix C.

4 Shapiro, Fair, and Rais 2011
is important because it provides the foundation for further research on how to best identify ‘game-changers’ in a given phenomenon under observation. Furthermore, none of the key findings outlined here could have been identified without introducing distinct breakpoints into the entire phenomenon under observation, disaggregating the Iraq Insurgency to reveal nuances in the baseline trajectory.

Finding 1: Escalating and De-escalating behavior

As shown in Table 5.1 and Table 5.2, a power law function provided marginally better fit during the escalatory segment of the Iraq insurgency as defined by Time Series 1 (T1) for both phases of observation. Results for Time Series 2 (T2) for both phases of observation show the exponential line to be an overwhelmingly better fit during the de-escalatory segment. The results demonstrate the Red Queen Hypothesis is a poor explanation for any point in time following the pre-\( n \) shift moment (shown here as T1). Even resetting the power law function as was done in T2 for both phases of observation does not result in a better fit during the de-escalatory segment. The implication here is that the Iraq Insurgency behaves differently during the escalation and de-escalation segments.
TABLE 5.1 - Phase 1, IED attacks (Breakpoint established at minimum value attained by CMA)*

<table>
<thead>
<tr>
<th>Phase 1 (IED)</th>
<th>Phase 2 (IED)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PLF</strong></td>
<td><strong>EXP</strong></td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td>Basra</td>
</tr>
<tr>
<td>Qadisiyah*</td>
<td>Baghdad</td>
</tr>
<tr>
<td>Ninawa</td>
<td>Basra</td>
</tr>
<tr>
<td>Diyala</td>
<td>Al-Tamim</td>
</tr>
<tr>
<td>Al Anbar</td>
<td></td>
</tr>
<tr>
<td><strong>TOTAL: 5</strong></td>
<td><strong>TOTAL: 4</strong></td>
</tr>
</tbody>
</table>

*Qadisiyah was excluded from Phase 1, T2 testing due to limited data points leading to inconclusive results

TABLE 5.2 - Phase 2, IED attacks (Breakpoint established at 1 January 2007)

<table>
<thead>
<tr>
<th>Phase 2 (IED)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PLF</strong></td>
</tr>
<tr>
<td>Al Anbar</td>
</tr>
<tr>
<td>Babil</td>
</tr>
<tr>
<td>Ninawa</td>
</tr>
<tr>
<td>Qadisiyah</td>
</tr>
<tr>
<td>Salah Ad Din</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>TOTAL: 5</strong></td>
</tr>
<tr>
<td><strong>TOTAL: 0</strong></td>
</tr>
</tbody>
</table>

Finding 2: Not all insurgencies behave the same

While five out of nine provinces are consistently better explained by a power law function during the escalatory segment across all phases of observation for IED attacks, the individual provinces differ between phases. Four provinces, however, remain constant across both phases of observation in following a power law function explanation during the escalatory segment of the insurgency—Salah Ad Din, Qadisiyah, Ninawa and Al Anbar.  

5 The five provinces that are better explained by a power law function during the escalatory phase consists of the four identified provinces (Salah Ad Din, Qadisiyah, Ninawa and Al Anbar) plus a fifth province that varies with each phase. For Phase 1, the fifth province better explained by a power law function is Diwali, whereas for Phase 2 it is Babil. See Appendix C.
A similar observation can be made about three provinces that are consistently better explained by an exponential fit across all phases of observations—Baghdad, At-Tamim and Basra. The observation that during the escalatory segment (T1), four provinces are consistently explained better by a power law function while three other provinces remain consistently better fit to an exponential explanation strongly suggests that not all insurgencies behave the same. Instead, there is sub-national variance across both individual provinces and groups of provinces when examining the Iraq Insurgency. This sub-national variance is not only evident in the manner by which individual provinces escalate, be it better explained by a power law function or exponential fit, but can also be observed when contrasting total hostile attacks against a 1-day data resolution.

Table 3.1 from Chapter 3 is reproduced here to demonstrate how contrasting the total reported hostile attacks with the 1-day data resolution applied in the original study reveal unique characteristics for individual provinces beyond just the escalatory process. Comparing IED attacks at a 1-day resolution (filtered) against the total number of casualties attributed to IEDs (unfiltered), some preliminary conclusions can be made regarding IED lethality across provinces. Whereas Al Anbar may be the most lethal, with 402 casualties attributed across 222 days with reported IED attacks, Qadisiyah and Salah Din are significantly less lethal.

Granted, the Red Queen Hypothesis examines power law functions at the individual province level, which may be seen as to implicitly acknowledge some level of

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6 It should be noted that this pattern holds across both phases for observation when examining IED attacks and all hostile attacks. See Appendix C.
sub-national variance. Its conclusions that a single escalatory process may be used to explain all provinces under observation, however, are contradicted by the findings from this paper’s study. Instead, the alternate study’s findings provide further vindication for those scholars who wish to take sub-national variance seriously.

<table>
<thead>
<tr>
<th>Province</th>
<th>IED (Filtered)</th>
<th>IED (Unfiltered)</th>
<th>ALL (Filtered)</th>
<th>ALL (Unfiltered)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Al Anbar</td>
<td>222</td>
<td>402</td>
<td>561</td>
<td>1144</td>
</tr>
<tr>
<td>At Tamim</td>
<td>25</td>
<td>44</td>
<td>43</td>
<td>70</td>
</tr>
<tr>
<td>Babil</td>
<td>57</td>
<td>96</td>
<td>103</td>
<td>178</td>
</tr>
<tr>
<td>Baghdad</td>
<td>445</td>
<td>778</td>
<td>653</td>
<td>1176</td>
</tr>
<tr>
<td>Basra</td>
<td>34</td>
<td>49</td>
<td>74</td>
<td>112</td>
</tr>
<tr>
<td>Diyala</td>
<td>78</td>
<td>133</td>
<td>127</td>
<td>216</td>
</tr>
<tr>
<td>Ninawa</td>
<td>54</td>
<td>77</td>
<td>129</td>
<td>204</td>
</tr>
<tr>
<td>Qadisiyah</td>
<td>15</td>
<td>17</td>
<td>24</td>
<td>28</td>
</tr>
<tr>
<td>Salah Din</td>
<td>127</td>
<td>178</td>
<td>222</td>
<td>319</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1057</strong></td>
<td><strong>1774</strong></td>
<td><strong>1936</strong></td>
<td><strong>3447</strong></td>
</tr>
</tbody>
</table>

Further research would benefit from examining these groups of individual provinces with similar escalatory behavior to identify different pathways by which insurgencies may proceed over time.

Finding 3: Scale Invariance

Results from conducting Phase 1 testing for all hostile attacks suggest a scale invariant nature for the Iraq Insurgency during the escalatory segment that is independent of the particular weapon system. As noted in Table 5.1, five out of nine provinces are better explained by a power law function during the escalatory segment. Similarly, Table 5.3 demonstrates that when all attacks are observed, five out of nine provinces are better
explained by a power law function during the escalatory segment. At the individual province level, four provinces are better explained by a power law function across both phases, regardless of whether all attacks or only IED events were under observation—Al Anbar, Ninawa, Diyala and Salah Ad Din. Additionally, three provinces are better explained by an exponential fit across both phases, regardless of whether all attacks or only IED events were under observation—Baghdad, Basra and At-Tamim. The implication here is that while not all insurgencies behave the same, the results from this study suggest that they maintain certain internally consistent traits. One such trait is the scale invariant nature as observed by the internally consistent behavior for individual provinces, regardless as to whether hostile attacks are observed in aggregate or isolated to a particular weapon system. Further research would benefit from focusing on possible causal mechanisms that may explain internally consistent behavior across phases of observation.

**TABLE 5.3 - Phase 1, all attacks (Breakpoint established at minimum value attained by CMA)**

<table>
<thead>
<tr>
<th>Province</th>
<th>T1</th>
<th>T2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Al Anbar</td>
<td>Baghdad</td>
<td>Al Anbar</td>
</tr>
<tr>
<td>Babil</td>
<td>At-Tamim</td>
<td>Qadisiyah</td>
</tr>
<tr>
<td>Ninawa</td>
<td>Basra</td>
<td>Baghdad</td>
</tr>
<tr>
<td>Diyala</td>
<td>Qadisiyah</td>
<td>Salah Ad Din</td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td>TOTAL: 6</td>
<td>TOTAL: 7</td>
</tr>
</tbody>
</table>

Implications

While the Red Queen Hypothesis only addresses the escalatory segment of the Iraq Insurgency, the study presented here speaks to the entire phenomenon under observation from 2003 to 2010. By incorporating two distinct breakpoints, one indications-driven and the other event-based, this study successfully captures a departure
from the baseline trajectory over time. Or, put another way, this study identifies a ‘game changer’ in the Iraq Insurgency. By examining the entire phenomenon, this study is capable of identifying changes in the baseline trajectory whereas the Red Queen Hypothesis is censored at the point in which the baseline trajectory is no longer applicable. It is the point of discontinuity, captured in this study by the de-escalatory segment (T2) across all phases of observation, which is of the utmost concern from a policy standpoint. In this particular case, discontinuity from the baseline trajectory is the desired policy outcome—slowing the insurgency’s frequency and escalation of hostile attacks over time.

Testing across both phases of observation reveal similar characteristics with policy implications directly applicable to establishing distinct breakpoints and identifying ‘game-changer’ events. It is important to remember that the methodological difference between Phase 1 and Phase 2 testing is found in what type of distinct breakpoint was used to separate the data. While Phase 1 testing relied upon an indications-driven breakpoint established by identifying the minimum value attained by the cumulative moving average for τ, Phase 2 testing used an event-date. Results from both phases, however, captured similar observations regarding the phenomenon’s changing nature over time. Most notably, testing from both phases displayed T2 results that overwhelmingly aligned with an exponential fit over that of a power law function. The key implication here is that both types of breakpoints were broadly successful in observing a fundamental departure in the phenomenon’s path from its baseline trajectory—effectively identifying a ‘game changer.’
This is important and warrants further investigation for two main reasons. First, it is conceivable change in a phenomenon over time may occur by unidentified means. In such instances, developing indications to effectively capture this change may be absent or incomplete. The Phase 2 results, however, suggest it may still be possible to identify changes in the baseline trajectory by establishing a distinct breakpoint surrounding key event-dates relevant to the phenomenon under observation. In the case of this study, 1 January 2007 was used to capture possible changes in the Iraq Insurgency caused by increased troop levels with the adoption of a new strategy. Presumably, if the 2007 troop surge had no influence over the frequency and escalation of hostile attacks in Iraq, then there would have been no significant distinction between T1 and T2 results. While indications-driven breakpoints should be seen as more accurate from a methodological standpoint, the policy implication here is that event-based breakpoints may be an adequate substitution when the changing nature for the phenomenon under observation is unknown.

Although not the central focus for the original study, Johnson’s use of cumulative moving averages to effectively censor his dataset to strictly the escalatory segment in the Iraq Insurgency warrants further investigation. Figure 5.1 displays the cumulative moving average for the frequency of all hostile attacks measured by calendar days in Salah Ad Din Province from 2003 to 2010.
As Figure 5.1 demonstrates, there is an escalatory and de-escalatory segment separated by the distinct breakpoint established at the minimum value attained by the cumulative moving average. Whereas the CMA values followed a generally negative trending prior to the breakpoint, a generally positive trending is observed afterwards. Perhaps counter-intuitively, a negative trending in cumulative moving averages indicates hostile attacks are occurring more frequently over time and therefore the insurgency is escalating. A positive trending, therefore, indicates attacks are occurring less frequently and that the insurgency is de-escalating. There are two key implications that can be taken by observing the cumulative moving average charts for individual Iraqi Provinces. First, observing the cumulative moving average for the frequency in hostile attacks for each individual province included in the original study shows the Iraq Insurgency goes through
a distinct escalatory and de-escalatory segment over time. Or, put another way, the Iraq Insurgency can be broadly separated into a period of time where coalition military forces were losing and a period of time where they were winning. The fluctuations in the cumulative moving average likely reflect the tactical victories and defeats that can be expected as insurgents and coalition military forces engage over time.

Second, as Figure 5.1 demonstrates by displaying the breakpoint for Salah Ad Din, some individual provinces began to experience a declining frequency for hostile attacks prior to the troop surge. As stated earlier, this study is interested in identifying departures from the baseline trajectory but does not establish the causal mechanisms for the discontinuity. It should be noted that six out of nine provinces have indication-driven breakpoints after 1 January 2007, as shown in Table 5.4. This may be expected when one considers the temporal lag that should be expected after implementing a new strategy.\textsuperscript{7} Further research, however, would benefit from examining why some provinces appear to have seen a de-escalation in hostile attacks prior to either the troop surge or Sunni Arab Awakening—broadly speaking, two common narratives for explaining declining violence in Iraq.\textsuperscript{8}

\textsuperscript{7} For further discussion on how time influences social processes, see Pierson 2004.

\textsuperscript{8} For further research that examines possible explanations for declining violence in post-2007 Iraq, see Biddle, Friedman, and Shaprio 2012.
TABLE 5.4: Phase 1, T1 Break Points for Individual Iraqi Provinces

<table>
<thead>
<tr>
<th>IRAQI PROVINCE</th>
<th>DATE FOR MINIMUM VALUE ATTAINED BY CMA (BREAKPOINT, PHASE 1, T1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diyala</td>
<td>18 June 2004</td>
</tr>
<tr>
<td>Ninawa</td>
<td>28 May 2005</td>
</tr>
<tr>
<td>Salah Ah Din</td>
<td>1 January 2006</td>
</tr>
<tr>
<td>Al Anbar</td>
<td>23 March 2007</td>
</tr>
<tr>
<td>Qadisiyah</td>
<td>14 June 2007</td>
</tr>
<tr>
<td>Babil</td>
<td>25 June 2007</td>
</tr>
<tr>
<td>Basra</td>
<td>7 August 2007</td>
</tr>
<tr>
<td>Baghdad</td>
<td>10 October 2007</td>
</tr>
<tr>
<td>At Tamim</td>
<td>12 October 2007</td>
</tr>
</tbody>
</table>

Ultimately, the results from this paper challenge the Red Queen Hypothesis as they proceed to put forth policy-relevant findings. Introducing distinct breakpoints into the entire phenomenon under observation revealed an alternate narrative for understanding insurgency. Insurgencies do not escalate in the same way by which they may later de-escalate. There is sub-national variance across provinces that demonstrate not all insurgencies behave alike. In both cases, these results are reflective of changes in the observed phenomenon over time. More tellingly, both may be considered instances whereby past behavior is not the best predictor of future action when viewed in
aggregate. Instead, these findings reflect departures from the baseline trajectory—
discontinuities which are not accounted for in the original aggregated extrapolation
model. The most compelling implication to be taken from these results is that
indications-driven breakpoints may provide a useful mechanism for identifying ‘game
changers.’
CHAPTER SIX: CONCLUSION

Returning to the two illustrations provided in the introduction, there is a key policy question to be found in the success and failure of extrapolations in Kunduz Province. Is the phenomenon under observation akin to the enemy mortar team that repeatedly attacked from the same location at the same time, or more closely aligned with the tactical innovation displayed in the siege of the Afghan National Army recruiting center? In one instance, short-term tactical extrapolations aided in the decision-making process necessary to disrupt insurgent activity, whereas the latter case all but ensured strategic surprise.

Ultimately, what this paper provides is an alternative study that examines aggregated extrapolation models in a new light. Instead of supposing past behavior is the best predictor for future action, this paper offers the more useful analytic query is to actively seek out when present behavior is no longer explainable by past action. This discontinuity represents a departure from the established baseline trajectory, effectively a ‘game changer’ event for the phenomenon under observation. Furthermore, it is only upon disaggregating the data that nuances in the trajectory are revealed. Identifying these changes in the established baseline trajectory over time provides an opportunity for further research on how to best detect indicators for impending ‘game changers.’
The central proposal made in this paper is that the introduction of distinct breakpoints into an aggregated extrapolation model will reveal changes in the phenomenon over time that would otherwise be masked by the baseline trajectory. This paper has offered distinct breakpoints as a methodology for examining how a phenomenon changes over time using two distinct techniques. Phase 1 procedures used an indications-driven breakpoint to establish changes in the trajectory over time using previously established measurements. Phase 2 procedures, however, used an event-based breakpoint positioned at a point in time assessed to be significant to the phenomenon under observation. The initial results presented by this study suggest that while indications-driven breakpoints are more accurate in identifying impending change in the established baseline trajectory, event-based breakpoints may provide an adequate alternative when the nature of how the phenomenon is likely to evolve remains unknown. Determining points of departure along an established baseline can alert policymakers to impending change. Providing observable and measurable indicators to identify these breakpoints, be they indications-driven or event-based, before they substantially change the event’s trajectory is both interesting and highly relevant.

Furthermore, in doing so, this study provides key findings for the Iraq Insurgency that are otherwise masked in the original study. The process by which the Iraq Insurgency escalated was characteristically different than how it de-escalated. Examining individual provinces across phases of observation revealed a level of sub-national variation also not evident in the original study. Only the last finding, pointing to the scale invariant nature for escalation in hostile attacks independent of the weapon
system employed, falls within the explanatory framework established by the Red Queen Hypothesis.

A key finding observed in the original study, further examined in the alternate study described in this paper, is that the cumulative moving average for the frequency in hostile attacks serves as an effective indication to identify change in the insurgency’s trajectory over time. The minimum value attained by the cumulative moving average, though the terminal endpoint for the original study, serves as a distinct breakpoint for the alternate study that allows for observation of the entire Iraq Insurgency through both escalatory and de-escalatory segments.

While further research is required, the findings from this study demonstrate promising results that hold external validity for other insurgencies. An examination of Kandahar Province in accordance with the original study is displayed in Figure 6.1. Important to note here is that the period of observation for Kandahar is 2001 through 2010, and that the entire period of observation for Kandahar Province is one of an escalating insurgency, as demonstrated in Figure 6.2.
Whereas the Iraq Insurgency displayed distinct escalatory and de-escalatory segments across all nine provinces under observation, hostile attacks in Kandahar reflect a continually escalating insurgency. Or, put another way, the central policy implication for Figure 6.2 is that coalition military forces have never been winning in Kandahar.\(^1\) While Figure 6.2 suggests coalition military forces have never been winning in Kandahar, an examination of hostile attacks during the same time period in Zabul province offers a different narrative.

---

\(^1\) Casualty data was examined for Kandahar Province from 2010 to 2012 in order to allow for any post-surge effect on the insurgency’s trajectory. Examining hostile attacks in Kandahar Province from 2001-2012, as well as isolating the post-surge time period of 2010-2012, revealed no change in the overall trajectory for the escalating insurgency. It should be noted that examining hostile attacks in Helmand Province from 2010 through 2012 revealed a de-escalating insurgency, however, when all hostile attacks for the province were examined from 2001-2012 no such change in trajectory occurred. A possible explanation for the observed de-escalatory segment in Helmand Province from 2010-2012 may include the impact from Operation ‘Moshtarak,’ a major ISAF and ANSF offensive targeting the Taliban stronghold in the city of Marjah. For more information on this operation, please see Chivers and Filkins 2010.
As shown in Figure 6.3, hostile attacks in Zabul Province experienced distinct periods of escalation and de-escalation. Specifically, hostile attacks 6-12 which corresponds to September 2005 to March 2008 is a de-escalatory period for the insurgency in Zabul.
This ultimately raises a key observation and an important policy implication. First, Afghanistan displays sub-national variation when examining the frequency and escalation of hostile attacks at the provincial level. Consequently, Zabul does not fit the model provided in the original study since a power law function does not display better fit than an exponential curve. Proponents of the original study may respond that the Red Queen Hypothesis, while the superior model, does not address all cases, noting it is better in 70% of the provinces under observation. Zabul, then, would fall into the 30% of provinces that fail to be adequately explained by the Red Queen Hypothesis. This sub-national variation, however, does have an important policy implication. Zabul does not fit the Red Queen Hypothesis because, for a period of time between 2005 and 2008, coalition military forces were winning—the insurgency was in a de-escalatory phase. The question then becomes, did coalition military forces know they were winning in Zabul Province at the time they were doing so? The study presented in this paper provides the foundational research agenda to pursue the broader query presented by this question—how to identify impending departures from the baseline trajectory.

In its present state, the study presented in this paper provides a retrospective analysis for assessing whether a phenomenon under observation is in accordance with or a departure from the established trajectory. Future research should be dedicated to incorporating a predictive element into the study’s methodology. Doing so would both be more interesting and possess greater policy implications. Ten years of armed conflict, arguably the most collected-upon and reported war in human history, present an opportunity for greater understanding of political violence. One of the more interesting

2 Johnson et al. 2011a, 81
questions begins not by looking to the past to explain the future, but rather actively seeking out when the present departs along an alternate path.
REFERENCES


Grabo, Cynthia M. *Anticipating Surprise: Analysis For Strategic Warning*. Joint Military Intelligence College's Center for Strategic Intelligence Research, 2002.


APPENDIX A: PHASE 1 IRAQ PROVINCE-LEVEL IED ATTACKS

Al Anbar Province

<table>
<thead>
<tr>
<th>Phase 1</th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.1568858214</td>
<td>0.1168772334</td>
</tr>
<tr>
<td>T1e</td>
<td>0.1084988551</td>
<td>0.2403059433</td>
</tr>
<tr>
<td>DELTA</td>
<td>0.0483669663</td>
<td>0.1234287099</td>
</tr>
<tr>
<td>DELTA/T1p</td>
<td>0.3084215378</td>
<td>0.5136315324</td>
</tr>
</tbody>
</table>
## At-Tamim Province

### Phase 1

<table>
<thead>
<tr>
<th></th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.148879839</td>
<td>0.0032108005</td>
</tr>
<tr>
<td>T1e</td>
<td>0.2392504376</td>
<td>0.0640263727</td>
</tr>
<tr>
<td>DELTA</td>
<td>0.0903705986</td>
<td>0.0608155722</td>
</tr>
<tr>
<td>DELTA/T1e</td>
<td>0.3777238592</td>
<td>0.9498519069</td>
</tr>
</tbody>
</table>
Babil Province

\[
\begin{align*}
\text{Babil Province} & \\
\text{Phase 1} & \\
\text{T1 R-Squared Comparison} & \quad \text{T2 R-Squared Comparison} \\
T1p & 0.1095468699 & T2p & 2.99202E-005 \\
T1e & 0.1301142115 & T2e & 0.032286828 \\
\text{DELTA} & 0.0205673416 & \text{DELTA} & 0.0322569078 \\
\text{DELTA/T1e} & 0.1580714463 & \text{DELTA/T2e} & 0.9990733012
\end{align*}
\]
Baghdad Province

### Phase 1

<table>
<thead>
<tr>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.1339241885</td>
</tr>
<tr>
<td>T1e</td>
<td>0.140832174</td>
</tr>
<tr>
<td>DELTA</td>
<td>0.0069079855</td>
</tr>
<tr>
<td>DELTA/T1e</td>
<td>0.0490511884</td>
</tr>
</tbody>
</table>
British forces served as the dominant military presence in Basra up until their 2007 withdrawal. Logically, as demonstrated by Phase 1 T2 testing, significantly reducing troop levels will necessarily reduce the number of hostile attacks measured by coalition military casualties. See Farrell 2007.
Diyala Province$^2$

<table>
<thead>
<tr>
<th>Phase 1</th>
<th>T1 R-Squared Comparison</th>
<th>T1 (A) R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.0522878221</td>
<td>T1(A)p</td>
<td>0.1649395659</td>
</tr>
<tr>
<td>T1e</td>
<td>0.014206914</td>
<td>T1(A)e</td>
<td>0.1496316198</td>
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<td>DELTA</td>
<td>0.0380071307</td>
<td>DELTA</td>
<td>0.0353679481</td>
</tr>
<tr>
<td>DELTA/T1p</td>
<td>0.7268830327</td>
<td>DELTA/T1pa</td>
<td>0.1911785356</td>
</tr>
</tbody>
</table>

$^2$ Diyala province is the only such province identified in the original study as having two minimum values attained by the cumulative moving average. Consequently, Phase 1 testing includes time series for both minimum values (T1 and T1A). Phase 2 testing, however, uses 1 January 2007 as a distinct breakpoint and therefore does not include any additional time series.
Ninawa Province is the only case examined in which the observed trajectory reflects a de-escalating insurgency prior to the breakpoint, and an escalating insurgency after the breakpoint. See also Ninawa Province during Phase 2 testing on pg 60 (Appendix B)
Qadisiyah Province

Qadisiyah was removed from consideration when counting the total number of provinces which were best explained by either a power law function or exponential fit during Phase 1 T2 testing due to the limited data points.

---

4 Qadisiyah was removed from consideration when counting the total number of provinces which were best explained by either a power law function or exponential fit during Phase 1 T2 testing due to the limited data points.
Salah Ad Din Province

<table>
<thead>
<tr>
<th>Phase 1</th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.0536756123</td>
<td>0.0298728092</td>
</tr>
<tr>
<td>T1e</td>
<td>0.0213557533</td>
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<tr>
<td>DELTA</td>
<td>0.032319859</td>
<td>0.0322649034</td>
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<tr>
<td>DELTA/T1p</td>
<td>0.6021330287</td>
<td>0.5192483284</td>
</tr>
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</table>
APPENDIX B: PHASE 2 IRAQ PROVINCE-LEVEL IED ATTACKS

Al Anbar Province

![Graphs showing IED attacks in Al Anbar Province during Phase 2]

<table>
<thead>
<tr>
<th>Phase 2</th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.157596013</td>
<td>0.149435291</td>
</tr>
<tr>
<td>T1e</td>
<td>0.109968076</td>
<td>0.257282707</td>
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<tr>
<td>DELTA</td>
<td>0.047627936</td>
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</tr>
<tr>
<td>DELTA/T1p</td>
<td>0.302215363</td>
<td>0.419178645</td>
</tr>
<tr>
<td>DELTA/T2e</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
At-Tamim Province

Phase 2

<table>
<thead>
<tr>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.077366337</td>
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<tr>
<td>T1e</td>
<td>0.1202904906</td>
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<tr>
<td>DELTA</td>
<td>0.0429241536</td>
</tr>
<tr>
<td>DELTA/T1e</td>
<td>0.3568374639</td>
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</table>
Babil Province

Phase 2

<table>
<thead>
<tr>
<th></th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.0368180843</td>
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<td>T1e</td>
<td>0.0239641327</td>
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<tr>
<td>DELTA</td>
<td>0.0128539516</td>
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<tr>
<td>DELTA/T1p</td>
<td>0.3491205978</td>
<td>0.6525350029</td>
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</table>
Baghdad Province

**Graphs:**
- **Iraq IED Attacks**
  - Baghdad (Phase 2, T1 Power Law Function)
  - Baghdad (Phase 2, T1 Exponential Fit)
- **Post-Surge Hostile Attacks**
  - Baghdad (Phase 2, T2 Exponential Fit)

**Phase 2**

<table>
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<tr>
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<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
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<td>DELTA/T1e</td>
<td>0.1864008802</td>
<td>0.6647828854</td>
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</table>
Basra Province

<table>
<thead>
<tr>
<th>Phase 2</th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
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<td>8.10428E-005</td>
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<td>T1e</td>
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<tr>
<td>DELTA/T1e</td>
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<td>0.3387210253</td>
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<tr>
<td></td>
<td></td>
<td></td>
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</tbody>
</table>
Diyala Province

<table>
<thead>
<tr>
<th>Phase 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1 R-Squared Comparison</td>
</tr>
<tr>
<td>T1p</td>
</tr>
<tr>
<td>T1e</td>
</tr>
<tr>
<td>DELTA</td>
</tr>
<tr>
<td>DELTA/T1e</td>
</tr>
</tbody>
</table>
Ninawa Province

**Phase 2**

<table>
<thead>
<tr>
<th></th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
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<td>0.16229842</td>
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<td>DELTA</td>
<td>0.0168523008</td>
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<tr>
<td>DELTA/T1p</td>
<td>0.2448185455</td>
<td>DELTA/T2e</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.2369635647</td>
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</tbody>
</table>
Qadisiyah Province

<table>
<thead>
<tr>
<th></th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.1325206973</td>
<td>0.2345269422</td>
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<td>T1e</td>
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<td>0.3093606208</td>
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<tr>
<td>DELTA</td>
<td>0.1002332427</td>
<td>0.0748336786</td>
</tr>
<tr>
<td>DELTA/T1p</td>
<td>0.7563591555</td>
<td>0.2418978809</td>
</tr>
</tbody>
</table>
Salah Ad Din Province

<table>
<thead>
<tr>
<th>Phase 2</th>
<th>T1 R-Squared Comparison</th>
<th>T2 R-Squared Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1p</td>
<td>0.0144150162</td>
<td>0.0495467251</td>
</tr>
<tr>
<td>T1e</td>
<td>0.0001853188</td>
<td>0.137123333</td>
</tr>
<tr>
<td>DELTA</td>
<td>0.0142296974</td>
<td>0.0875766079</td>
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<tr>
<td>DELTA/T1p</td>
<td>0.987144045</td>
<td>0.638670356</td>
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</table>
APPENDIX C: IRAQI PROVINCE-LEVEL RESULTS (PHASE 1 AND 2)

Tables C.1-C.4 show the Iraqi Province-Level results by phase, time series, and weapon system (IEDs or all hostile attacks) for comparing r-2 squared values obtained by calculating the power law function and exponential fit (see Appendix A and Appendix B). Iraqi Provinces placed in the ‘PLF’ column were observed as having a higher r-2 squared value when a power law function was applied to the data, whereas those provinces placed in the ‘EXP’ column maintained a higher r-2 squared value with an exponential fit.

**TABLE C.1**

<table>
<thead>
<tr>
<th></th>
<th>PHASE 1 (IED)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PLF</td>
<td>EXP</td>
</tr>
<tr>
<td></td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td>Basra</td>
<td>Ninewa</td>
</tr>
<tr>
<td>Qadisiyah*</td>
<td>Baghdad</td>
<td></td>
</tr>
<tr>
<td>Ninewa</td>
<td>Babil</td>
<td></td>
</tr>
<tr>
<td>Diyala</td>
<td>Al-Tamim</td>
<td></td>
</tr>
<tr>
<td>Al Anbar</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL: 5</td>
<td>TOTAL 4</td>
<td>TOTAL 1</td>
</tr>
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</table>

**TABLE C.2**

<table>
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<tr>
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<tbody>
<tr>
<td></td>
<td>PLF</td>
<td>EXP</td>
</tr>
<tr>
<td></td>
<td>T1</td>
<td>T2</td>
</tr>
<tr>
<td>Al Anbar</td>
<td>Al-Tamim</td>
<td></td>
</tr>
<tr>
<td>Babil</td>
<td>Baghdad</td>
<td></td>
</tr>
<tr>
<td>Ninewa</td>
<td>Basra</td>
<td></td>
</tr>
<tr>
<td>Qadisiyah</td>
<td>Diyala</td>
<td></td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TOTAL: 5</td>
<td>TOTAL 4</td>
<td>TOTAL 0</td>
</tr>
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</table>
### TABLE C.3

**PHASE 1 (ALL)**

<table>
<thead>
<tr>
<th>PLF</th>
<th>EXP</th>
<th>PLF</th>
<th>EXP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Al Anbar</td>
<td>Baghdad</td>
<td>Babil</td>
<td>Al Anbar</td>
</tr>
<tr>
<td>Babil</td>
<td>Al-Tamim</td>
<td>Diyala</td>
<td>Baghdad</td>
</tr>
<tr>
<td>Ninawa</td>
<td>Bases</td>
<td></td>
<td>Al-Tamim</td>
</tr>
<tr>
<td>Diyala</td>
<td>Qadisiyah</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td>Ninawa</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**TOTAL: 5**

**TOTAL: 4**

**TOTAL: 2**

**TOTAL: 7**

### TABLE C.4

**PHASE 2 (ALL)**

<table>
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<tr>
<th>PLF</th>
<th>EXP</th>
<th>PLF</th>
<th>EXP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Babil</td>
<td>Baghdad</td>
<td>Al-Tamim</td>
<td>Baghdad</td>
</tr>
<tr>
<td>Baara</td>
<td>Al Anbar</td>
<td></td>
<td>Al Anbar</td>
</tr>
<tr>
<td>Salah Ad Din</td>
<td>Ninawa</td>
<td></td>
<td>Salah Ad Din</td>
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<tr>
<td></td>
<td>Diyala</td>
<td>Babil</td>
<td>Babil</td>
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<tr>
<td></td>
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<td>Qadisiyah</td>
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</table>

**TOTAL: 3**

**TOTAL: 6**

**TOTAL: 1**

**TOTAL: 8**
Tables C.5-C.6 provide cross-tabulated results taken from Tables C.1-C.4 for both IED attacks and all hostile attacks.

**TABLE C.5**

<table>
<thead>
<tr>
<th>Provinces</th>
<th>PHASE 1 (IED)</th>
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<th>T2</th>
<th>PHASE 2 (IED)</th>
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<th>T2</th>
</tr>
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<tr>
<td></td>
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<td>EXP</td>
<td></td>
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<td>EXP</td>
</tr>
<tr>
<td>Al Anbar</td>
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<td>Al-Tamim</td>
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<td>Salah Ad Din</td>
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</table>

**TABLE C.6**

<table>
<thead>
<tr>
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<th>T1</th>
<th>T2</th>
<th>PHASE 2 (ALL)</th>
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<th>T2</th>
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<tbody>
<tr>
<td></td>
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<td>EXP</td>
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<td>Salah Ad Din</td>
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