Countering the Adversary:

Effective Policies or a DIME a Dozen?

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Abstract: *This study uses counterfactual methodologies and empirical data to analyze the impacts of specific United States counter-insurgent (COIN) strategies on violent political conflict. The authors design a quasi-experiment in which they match cases across US Diplomatic, Information, Military, and/or Economic –DIME– actions (i.e., treatment variables) and then statistically analyze the impacts of such DIME actions on levels of political violence. For the purposes of this study the authors focus on the effects of military training in India and the impacts of other various DIME indicators on violence in the Philippines and Indonesia. The results reveal that some DIME actions have the expected effects while others have counterintuitive effects.*

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1.0 Introduction

How do we know if U.S. tactics and strategies work at countering the adversary? How do we know what would have happened if we *did not* implement a given action? Essentially, how can we estimate counterfactual outcomes? In this study, we use matching techniques (Ho, Imai, King, and Stuart 2005) coupled with counterfactual analysis to examine the impact of the stimulus on levels of violent political conflict. We focus on examining how U.S. military training impacted levels of violence by non-state actors in India as well as how US diplomacy and military actions impacted levels of violence in the Philippines. To do so, we use data that are extracted automatically from text which contain information on violent events as well as on the population's sentiment towards various actors such as the U.S., the host country's government, and the dissidents of interest. We then match our observations across the presence of a treatment variable such as the presence of military training, and estimate a model on the control group not experiencing the training. Using the model we generate a counterfactual series and compare it to the real data which did experience the treatment. The difference in the series is attributed to the effect of the treatment variable.

We begin by discussing the relevant literature on U.S. COIN strategies and tactics. We then move to articulating prominent theories of civil conflict. From there we explain our methodology and data in more detail. Results and a discussion of their implications for U.S. policy and future COIN analysis follows.

2.0 Identification & Significance of the Problem[1]

We contend that political conflict arises from the competition among political actors (governments, dissident groups, ethnic groups, religious groups, social groups, etc.) over policies, resources, territories, the state, and—especially—the support of the population. Such actors make

[1] Portions of the arguments made in this section reflect one of the author's main contentions with respect to violent political conflict and the literature on this topic. Some of the statements and verbiage appears in some of the author's previous solo-authored and co-authored papers (Shellman et al. 2010, Shellman 2008; Moore & Shellman 2008) as well as grant proposals and submissions.

strategic decisions as to how to behave towards one another and conflict escalates and de-escalates as a function of these interdependent decisions. Therefore, information on the myriad actors and their tactical decisions on a daily basis is needed to understand how strategies and tactics arise, change, succeed, and fail when confronted by the strategic and tactical choices of others – most notably the U.S.. Yet much of past conflict research has focused on the extent to which variation in the structural attributes of countries, such as their demographic characteristics and environmental conditions (e.g., GDP, urban population, and ethnic fractionalization levels) determine which are most likely to experience violent political conflict over time (Fearon and Laitin 1997). This fascination with the attributes of countries and perhaps even more so the widespread availability of cross-national "country-year" datasets has resulted in an opportunity cost. While we have much research focused on the structural conditions conducive to political conflict there are relatively few projects focused on the behavioral processes of conflict. In short, the "particularistic conceptualization" of conflict, driven by widely accessible country-year data sets, has become the default way to think about and study political struggles (see Moore 2006). This focus has made many students of conflict much less likely to explore conflict processes, actors' behavioral interactions, and the many choices available in the political arena that have effects on the ebb and flow of relative peace and violence. The many country-year conflict datasets (e.g., Armed Conflict Database, Correlates of War, International Crisis Behavior, etc.) at our disposal are ill-suited to study conflict processes which unfold over time and across space as a function of inter-linked decisions. We argue that political conflict is not best characterized as something that countries catch or experience. Conflicts spill across borders, involve ethnic and religious groups spanning multiple territories, and actors' decisions are certainly not made in annual intervals. The new generation of conflict scholarship recognizes that governments often face multiple challengers fighting for the same cause and/or very different causes, and that these challenges vary across both space and time (Shellman 2008). Given such realities, theorists have begun disaggregating the study of political conflict across actors, space and time. [2] We champion the

[2] See Shellman (2004a, 2004b, 2006a, 2006b, 2008, 2009); Shellman & Stewart (2007a; 2007b); Shellman, Hatfield, and Mills (2010); Moore & Shellman (2008); Moore (1998); Moore (2000).

approach to disaggregate conflict across actors, space and time in this project. Our theoretical framework focuses on the choices governments, dissidents, and other actors make rather than phases (e.g., "war") that emerge from structural characteristics of countries or the international system. Given our theoretical orientation, we must generate data on the day to day choices such actors make across space (not necessarily confined by state borders). Moreover, we should do this in a way that takes advantage of current and future technological developments and requires minimum human intervention – in particular unreliable human coding of data (Schrodt, Davis and, Weddle 1994).

In addition to disaggregating the study of political conflict into actors and their behavior, we also contend that support for actors' decisions and their tactics plays an important role in political and conflict dynamics. Mao Tse Tung (1966, 57) stated that "We must rely on the force of the popular masses, for it is only thus that we can have a guarantee of success." Che Guevara (1985, 50) followed by saying that "the guerrilla fighter needs full help from the people of the area. This is an indispensable condition…" and guerrillas must draw their "greatest force from the mass of the people." Lyndon Baines Johnson (1965) added "The ultimate victory will depend on the hearts and minds of the people." Finally, FM3-24 (2006, 1-28) states that "At its core, COIN [counterinsurgency] is a struggle for the population's support. The protection, welfare, and support of the people are vital to success. Gaining and maintaining that support is a formidable challenge." In sum, we know that support from the masses impacts political violence and politics more broadly. Yet, empirical studies are limited by a dearth of data to test how policies and actions shape attitudes and beliefs and how such attitudes and beliefs affect various actors' strategies, tactics, and actions. Historically, polls were the only means to measure and include such indicators in models of politics. However, polls are infrequent, expensive, and complicated to carry-out in certain locations. As a result, sentiment is difficult to measure in near real time and across space (cities, towns, regions, countries, etc.). Automating sentiment analysis can pay huge dividends in aiding our understanding of political dynamics, strategic communications, and effects based operations. To that end, Strategic Analysis Enterprises has developed state of the art event and sentiment coding software which makes use of advanced natural language processing algorithms to produce high quality event and sentiment data[3].

In a recent DARPA seedling, we showed that our newly generated sentiment data closely mirrors polling data and performs well in models of politics, increasing various models' explanatory power. That is, our models which include sentiment better explain and predict political behavior with less error than models which exclude such data. Through internal research and development efforts we also developed an event coder and results show that it is prone to less error and codes events more accurately than other current technologies.

In this project, we demonstrate how we use our tools to collect DIME data and then test their effects on political conflict using impact assessment and matched-case counterfactual models. Our project helps in planning and assessing course of action analysis by empirically modeling and testing which U.S. DIME actions "work" and which "fail." Moreover, we show how U.S. actions may have negative effects at the outset but over time, controlling for other factors, yield long term gains. Static models show one result while time-varying models show additional effects. How long does it take for military training efforts of a host nation to yield long-term benefits? While such training activities might exacerbate conflict in the near term, they may stabilize the conflict and lessen the intensity of the conflict over the long term. We provide evidence consistent with such a hypothesis in this paper.

Before moving to our methodologies, data, and results we begin with a discussion of DIME actions to motivate our analysis.

3.0 U.S. COIN/DIME Literature[4]

Since September 11, 2001, the military has become more interested than ever in conceptualizing the "operational environments" (OE) in which it is called upon to act. During the Cold War and prior to

[3] Shellman is President & CEO of Strategic Analysis Enterprises (SAE), Inc and his company developed SAEtext which is used in this project. SAE provides in-kind support to his NSF projects allowing members of his W&M team to use the software to produce data for analysis.

[4] Portions of this section draw heavily on one of the co-author's previous co-authored papers (Horne, Shellman & Stewart 2008) with permission from his co-authors.

September 11, the strategy set defining the OE was seen in terms of four primary, interconnected categories: Diplomatic, Informational, Military, and Economic (DIME) (FM 3-0, 2001). Military doctrine identified the DIME strategy set as the instruments of national power. Military doctrine construes each element of DIME as a system, such that a given DIME strategy set can be thought of as a "system of systems." In this sense strategies are directly associated with specific *capabilities*, and understanding one's own and an adversary's capabilities (*nodes* in the system) and the relationships among these nodes (*links* in the system) aids one in determining the best strategy combination in the given OE. Military doctrine describes the "nodes" and "links" of the system in these terms:

> "Each system in the operational environment is composed of various nodes and links. System *nodes* are the tangible elements within a system that can be "targeted" for action, such as people, materiel, and facilities. *Links* are the behavioral or functional relationships between nodes, such as the command or supervisory arrangement that connects a superior to a subordinate, the relationship of a vehicle to a fuel source, and the ideology that connects a propagandist to a group of terrorists" (JP 3-0, IV-4).

Following the onset of the U.S.'s War on Terrorism and a shift in focus from interstate warfare to intrastate, asymmetric warfare against insurgent groups, the military reconsidered its strategy set when facing such unconventional enemies. The result was DIMEFIL, an expansion of the original DIME concept, specifically designed for counterinsurgency operations (FM 3-24, 2006).[5] Under DIMEFIL, *Financial*, *Intelligence*, and *Law Enforcement* strategies are added to the choice set of U.S. instruments of power when confronting this type of adversary. The *Financial* instrument is similar to, but distinct from, the *Economic* instrument. Whereas the *Economic* instrument involves strategies such as trade sanctions and the control of sensitive exports, the *Financial* instrument targets the unique means by which insurgents acquire and distribute the capital means of conflict, including "formal banking, wire transfers,

[5] The acronym DIMEFIL was originally MIDLIFE, exposited in Interim Field Manual FMI 3-07.22, Counterinsurgency Operations, which expired October 2006.

debit and other stored value cards, online value storage and value transfer systems, the informal ‘hawala’ system, and cash couriers” (NMSP-WOT, 2006, 6).

Similarly, DIME’s *Information* instrument shares similarities to the *Intelligence* instrument articulated in DIMEFIL, though the former entails the effective use of information (about yourself and your adversary) in shaping public opinion and the enemy’s perspective on the conflict. *Intelligence*, on the other hand, deals in the mechanisms for collecting information relevant to a real or potential conflict. While intelligence operations were certainly an important part of Cold War strategies, DIMEFIL highlights the importance of *Intelligence* in counterinsurgency operations as a unique instrument of power. Whereas the Cold War offered a degree of stability via a balance-of-power logic, military counterinsurgency doctrine emphasizes the flexible and thereby unpredictable character of insurgent operations, justifying a more prominent role for intelligence. Likewise, *Law Enforcement* is regarded as an instrument of power unique to counterinsurgency, where national and international laws can be brought to bear to restore order domestically and ensure the legitimacy of a friendly government under pressure from insurgents (NSCT, 2006). While we have plans to explore many of these various instruments of power, for the purposes of this study we focus on U.S. military and diplomatic actions.

4.0 The General Model

Figure 1 contends that political dynamics affect popular support for the host government and competing dissident organizations and vice versa. Specifically, government and dissident interactions are public events and the population makes value judgments concerning those public interactions. As the dynamic of politics changes on the ground, how do organizations adapt and shift their tactics/strategies (military attacks v. attacks on civilians v. negotiations, etc.)? How do such dynamics affect public opinion (i.e., sentiment) and how does public opinion affect tactics and strategies? Finally, which U.S. tactics and strategies help win the support of the population and aid in defeating the insurgency? We discuss some of our preliminary results using this framework below to illustrate the utility that our approach and technological developments can have for understanding IW and SSTRO.

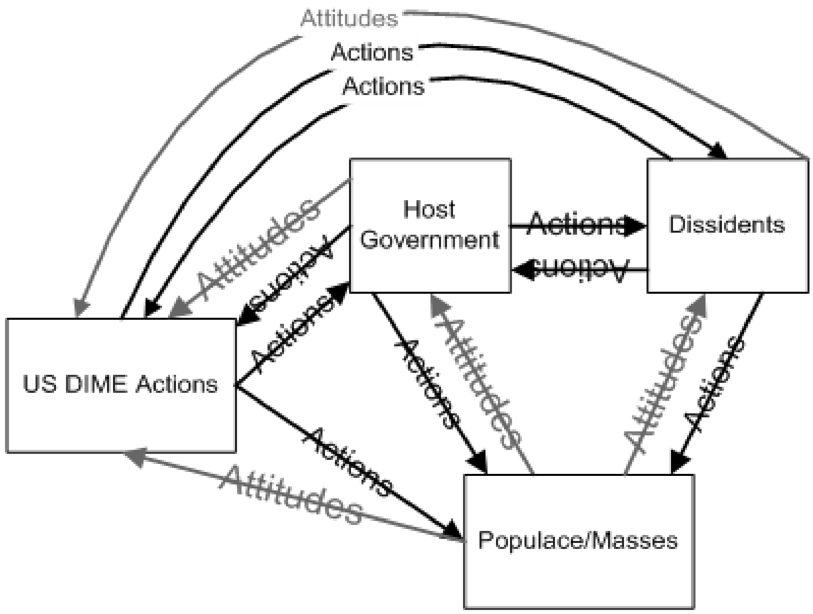

Figure 1 General Model of Political Dynamics and Popular Support

4.0 Data

The majority of our current data come from Shellman's (2008) Project Civil Strife datasets and the Integrated Crisis Early Warning System (ICEWS) datasets which were compiled from National Science Foundation (NSF) and Defense Advanced Research Projects Agency (DARPA) funded projects respectively. In total the projects generate several different but related datasets for 29 countries in the U.S. Pacific Command's (PACOM) south and southeast Asia region from 1997-2009. Without listing all 29, the dataset contains countries as diverse as Russia, Australia, Thailand, Indonesia, India, Nepal, the Solomon Islands, and the Philippines. The event data (dataset #1) contain information on daily events comprising information on "who did what to whom." The actors are disaggregated by individuals, groups, and branches of government, while the events are disaggregated by tactic and run the gamut from statements to negotiations to protests to armed clashes. Finally, the data also include international actions by all actors included in the 29 countries, as well as the United States and Europe. This dataset is two orders of magnitude greater than any other events dataset generated to date. While there are other global databases available, the ICEWS/PCS dataset contains information from over eight million news reports (over 25 gigabytes of English and translated foreign language text) from over 75 different news agencies.

A DARPA seedling project enabled SAE to develop an automated sentiment software package to generate sentiment data (dataset #2). The software generates "polling" type data in near real time from electronic sources such as blogs, Diaspora sources, and news reports. In short, the package incorporates a bag of words technique to quantify the perceptions of actors, policies and activities after texts have been sorted into such subtopics and sub-issues by a document classifier. Moreover, we built upon our event coding technologies to develop a dyadic sentiment coder in which we can collect information about one actor's attitudes towards another. No other packages that we know of currently generate this type of data; most utilize the bag of words technique and code the overall sentiment of a document without deciphering the actor doing the talking or the target of the sentiment. We have successfully integrated these data into various models to address how attitudes yield shifts in group goals, tactics, and strategies. In this project our goal is to assess what types of government behavior and policies produce shifts in various populations' attitudes and subsequently how such shifts in attitudes affect changes in dissident behavior (e.g., tactics and strategies). We use the dyadic sentiment data in this study.

4.1 Operational Indicators

In this section, we briefly sketch how we operationalize our concepts. In terms of the events data, we will aggregate the actions by individuals within groups, groups themselves, domestic governments, and international actors (governments, NGOs, and IGOs). For dissident actors and social groups we create violent, nonviolent, and cooperative event counts and weighted event counts (using well-known scales – e.g. Goldstein 1992 – to measure the intensity of actions) (See Shellman, et al. 2010 & Shellman 2006a & 2006b for examples). To operationalize U.S. government tactics, we use several indicators. To begin, we use Item Response Theory scaling (outlined in Horne, Shellman, and Stewart 2008) to create scales of relevant actors' diplomatic (D), information (I), military (M), economic (E), financial (F), intelligence (I), and law enforcement (L) or DIMEFIL activities. Essentially, the technique allows one to derive a latent variable (e.g., diplomacy) using the various “diplomatic events” contained in the events dataset. We can generate such domestic government oriented DIMEFIL activities as well as foreign government DIMEFIL activities, most notably the U.S. We estimate these dimensions using a two-parameter Bayesian IRT model. This framework allows us to estimate both the discrimination and the difficulty of the events along a latent dimension. That is, the two-parameter model estimates how ‘different’ various events are from each other as well how extreme or mild, for example, certain events are. This allows us to estimate scales that range from low level military conflict to more intense military conflict, for example, through the discrimination parameter and the rank order of events on this scale via the difficulty parameter. The Bayesian framework allows us to incorporate any prior information we may have regarding the scales we develop. This setup is also considerably more flexible than frequentist methods of dimensional extraction which often make assumptions of normality and linearity among scale items. Given the distribution of the events data, these traditional assumptions are almost certainly violated in ways that lead to biased results. Two-parameter models Bayesian IRT models have been used to estimate political parties’ left-right policy preferences (Bakker forthcoming, Armstrong and Bakker 2006), levels of democracy using Polity data (Treier and Jackman 2007), and measures of civil rights (Armstrong 2009). The resultant scales are essentially Likert-like scales ranging from -10 to +10 (strongly oppose to strongly support type measures).

In addition to creating scaled variables along a continuum, we isolate specific actions and estimate their impacts on adversarial activities. For example, in this study we examine the effects of specific military training exercises on the intensity of violent political conflict over time.

For this study, we aggregated the sentiment data into monthly temporal measures regarding the public’s attitudes towards specific actors. For example, we created dyadic measures representing the public’s attitudes towards the U.S. military, the Indian government, and Indian separatist groups. Having sketched the ways in which we operationalze data we turn towards our modeling capabilities.

5.0 Empirical Models: Impact Assessment Models & Counterfactual Models

What would happen to an ongoing insurgency if the United States began training the host government's military? How would positive diplomatic actions affect violent events on the ground? Such questions address complex cause-and-effect relationships which ultimately result in only one observable set of results. Either the U.S. decides to train a host nation's military to help quell an insurgency or it doesn't. A government either chooses to engage in positive diplomatic behavior or it doesn't. In either case, the observable data reflect only the course of action taken, but policy-makers may be deeply interested in knowing the (potential) outcome of the road not taken. But what if the U.S. did not train the host nation's military or rebuild infrastructure? Moreover, we want to know what the observable effects are from the road taken compared to the road not taken.

These "what if" type questions are quite common in the biological sciences and are often answered using natural experiments. For example, in a pharmaceutical trial one group of patients is given a new drug and designated the treatment group. A similar group of patients (in terms of characteristics, medical history, etc.), the control group, are administered only a placebo. Doctors can then estimate the average effect of treatment by comparing outcomes of the treatment and control groups. Social science questions often do not lend themselves to these kinds of natural experiments; anyone would agree that designing a foreign policy agenda around a natural experiment is a foolish course of action. However, using historical data we can leverage the insights of a natural experiment through case matching followed by statistical analyses. We can then estimate the effects of specific actions in various contexts.

What we have described above is termed "counterfactual analysis" and is based on the assumption that in scientific design every individual has an observed outcome and a potential outcome. We observe the effect of a treatment on individuals in the treatment group and assume that the outcome would have been different if that group had not received the treatment. Likewise, we observe outcomes for the control group and assume that outcomes would have been different if a treatment had been applied. More formally, we can write

$$\mathrm{T}_i = y_i^1 - y_i^0$$

where T_i represents the treatment effect for individual *i* and there are two possible outcomes y_i^1 and y_i^0 for every individual: y_i^1 is the outcome for individual *i* under treatment and y_i^0 is the outcome for individual *i* under no treatment.

If our subject has been given a treatment, then we observe y_i^1, and y_i^0, which is unobserved (counterfactual), is estimated from a model. The difference between these two outcomes is the treatment effect (T) for this subject.

Estimating treatment effects in experimental studies where the researcher can randomly assign the treatment is different from estimating effects with observational data – such as the data typically used to address our original questions regarding military training or positive diplomatic actions. For this kind of analysis, we combine counterfactual analysis with a case matching procedure. A concrete example will illustrate this process.

Suppose we want to know the effect of a military training exercise in India on violent attacks by insurgents. We have observational data on violent attacks and we know when military training exercises were conducted. Using military training as our treatment, we can look at the impact of training on the number of violent attacks per month before and after training. Of course, military training is not the only factor that might influence the number of violent attacks we observe. Models of political conflict suggest that government repression, government crackdown on insurgent groups, public sentiment, the economic and social environments, and other variables also shape conflict. Thus, we must control for such factors. To isolate the independent effect of our treatment – military training – we use matched case analysis, matching observations on these control variables.

We begin by fitting a model on all cases. We desire a model where the model-predicted values and the actual values correlate at a high value (.80-.99). Generating such a model provides increased confidence that we have not omitted important variables and provides a starting point for matching cases. The goal of matched case analysis is to choose cases which are as similar as possible on all confounding factors except the treatment variable. So for instance, we would choose to match pre-treatment months to post-treatment months that have similar values on government repression, government toward insurgent violence, and public sentiment. Combining a matched case analysis approach with counterfactual modeling increases our confidence that observed differences in the number of attacks before and after treatment are due to treatment, in this case, military training, and not confounding factors.

Figure 2 illustrates the basic tenants of the process. First we determine the dependent variable we wish to analyze. For our purposes it could be a stability indicator or the number of violent attacks. We will use violent attacks for illustrative purposes here. Second we fit a model to that dependent variable. The better the model, the more confident our inferences will be in determining the impact of a specific U.S. action. Third, we determine a treatment variable of interest – perhaps a specific DIME action such as training the military but such treatment variables could be as specific as carrying out a raid in a particular village. We then divide all of our cases by the treatment variable such that we have data on violent attacks that took place without any U.S. military training and data on violent attacks that took place in the presence of U.S. military training. Next, we match those cases on the control variables such as levels of repression, economic characteristics, social characteristics, previous dissident violence, etc. In each instance of matching, we will end up with cases that do not match up and we discard those cases. We use multiple matching algorithms such as nearest neighbor propensity score matching, exact matching, and genetic algorithms. We then choose the algorithm that provides the best matched set of cases and we use various quantitative measures to determine how well these cases match up. Given the technique, however, we do not need the cases to match-up 100% because we then model these data as opposed to doing a simple difference of means test. The model controls for error in the matching process. Once we have a matched set of cases, we run a statistical model on the cases that did not experience the treatment (control group). The model will vary based on the properties of the dependent variable. For example, if the data are counts we may use a negative binomial model, if the data contain many zeros because there are many days or weeks without attacks in the dataset, we may use a zero-inflated model, we could estimate a Bayesian model or a hidden Markov model. The model should best fit the properties of the dependent variable.

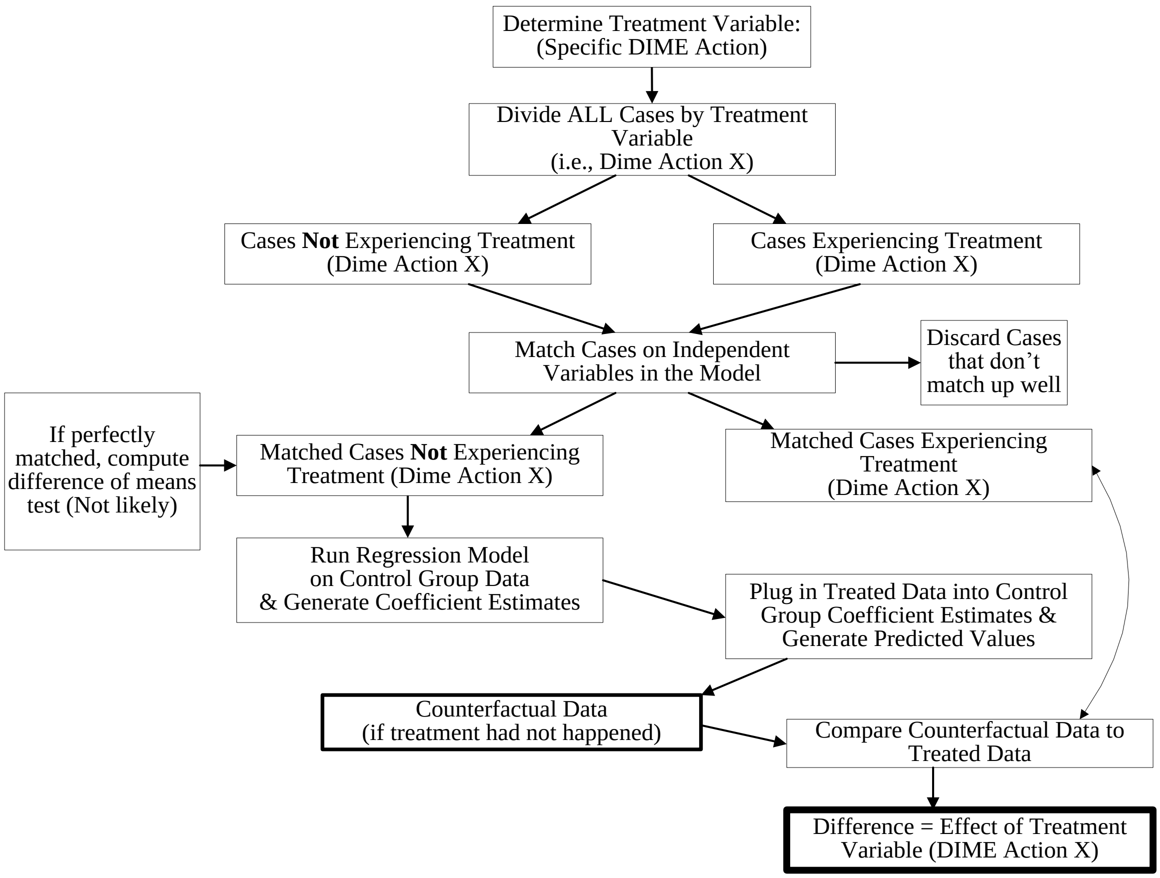

Figure 2 The Matched-Case Counterfactual Process

Once we have estimated the model we derive the parameter estimates from the untreated control group. We then apply those estimates to the treated group data to generate "predicted values." If this was a linear regression model, we would multiply each observation for each variable by its estimated coefficient estimate and add them together to produce the predicted value for that observation. These predicted values represent the "counterfactual" series. If the treatment effect has no impact, the counterfactual series should be equivalent (or statistically insignificant) to the control group series. If the data for the dependent variable are the same across the cases, there is no effect. However, if those data differ given our model, methodology, and our controls, we can attribute that difference to the treatment variable. An example follows.

In addition to the matched case counterfactual methods, we also employ time-series impact assessment methodologies. It is a complementary method and if we draw the same inferences across techniques we have increased confidence in our results. Impact assessment methodologies essentially code the presence of a particular action over time (e.g., military training exercise) and estimates the impact of that action within the confines of a statistical model shown to model the variance in a dependent variable of interest (e.g., violent attacks). One of the useful properties of such models is its ability to track impacts over time and vary the functional form of the relationship to uncover the best fitting curve (See Wood 1988; Shellman & Stewart 2007a). For example, does military training quell violent attacks overtime, does it first increase and then decrease them, do the two variables exhibit a long-run polynomial relationship? The impact assessment models allow for such analysis and the model provides insight into where such uncovered relationships are by chance or are statistically significant. We illustrate both techniques below.

6.0 Military Training in India

For our pilot study, we examined the impact of U.S. military training in India. The training exercises included the Malabar naval training exercises, COPE air force training, and 14 army training exercises. These exercises took place more or less constantly between 2002 and 2006. We can divide these up in the future and examine specific training exercises but for this study we grouped them together. While we examined several dependent variables, we will concentrate on the findings for violent attacks by separatist groups in India. Note that we can isolate specific groups (e.g., JKLF, New People's Army, etc.) in the future and/or explore different dependent variables.

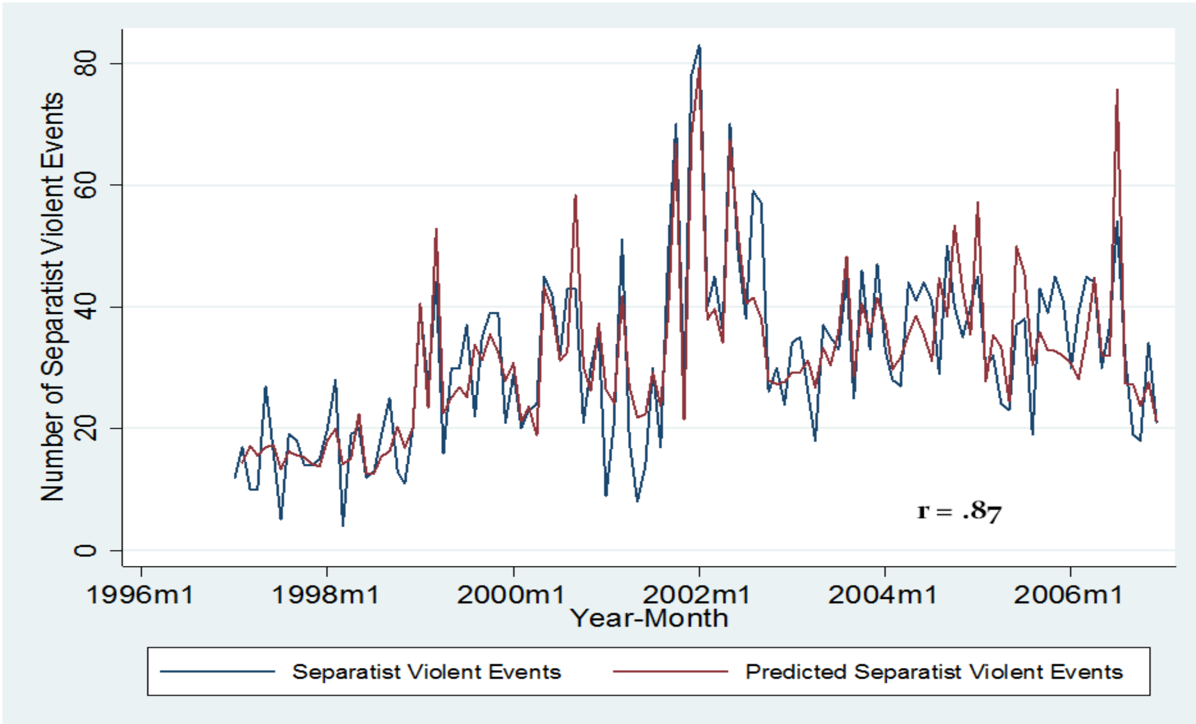

Figure 3 The Model-Predicted and Actual Separatist Violent Events: India 1997-2006

Figure 3 plots our negative binomial model predicted values against the actual values for the number of violent events carried out by separatists in India. The two series correlate at .87 indicating that our model does a very good job at explaining the variance of such violent events overtime. After settling on our model, we then split our cases up across the treatment variable: military training exercises carried out between early 2002 and 2006. We matched our observations on each variable in our model (e.g., government repression, human rights abuses, separatist nonviolent and cooperative actions, levels of democracy, economic indicators such as unemployment and inflation, and societal sentiment towards the government and the separatists) across the treatment variable. In this instance a genetic algorithm provided the best results in terms of maximizing "balance" across the cases.

Table 1 Percent Balance Improvement Between Treated and Control Groups for India Military Training Model*

	Genetic Matching
Distance (Overall Improvement)	94.37
Sentiment to Separatist	89.91
Sentiment to Government	62.9
Separatist Low Cooperation	82.38
Separatist Med. Cooperation	88.71
Separatist Low Hostility	91.66
Separatist High Hostility	45.61
Gov. to Separatist Hostility	98.33

*Selected input variables

Table 1 displays the balance improvement overall (i.e., distance) and for each independent variable. Balance (i.e., how evenly matched the cases are across the variables) improved upwards of 98% for some variables and only as little as 45% for others. The overall propensity score (i.e., distance) yielded a high value (94%) indicating that the cases were well matched. If we had obtained perfect matches, there would be no need to perform additional analyses on the data. We could simply perform difference of means between the control and treatment group. However, since we did not achieve perfect balance, the matching procedure can be thought of as a method of pre-processing the data prior to traditional parametric analysis. Once we obtained our matched cases, we applied our core model to the control group and predicted a counterfactual series using the coefficients from this model and data from the treatment group. Figure 4 shows the counterfactual series overlaid on the actual series of separatist violence events. The figure highlights the 1.92 difference in attacks during the military training period. That is, U.S. military training exercises in India increase separatist violent events (controlling for other factors) by about 2 violent events per month. Two fewer violent events would have transpired per month if U.S. military training had not occurred between 2002 & 2006. The effect is statistically significant at the 95% level.

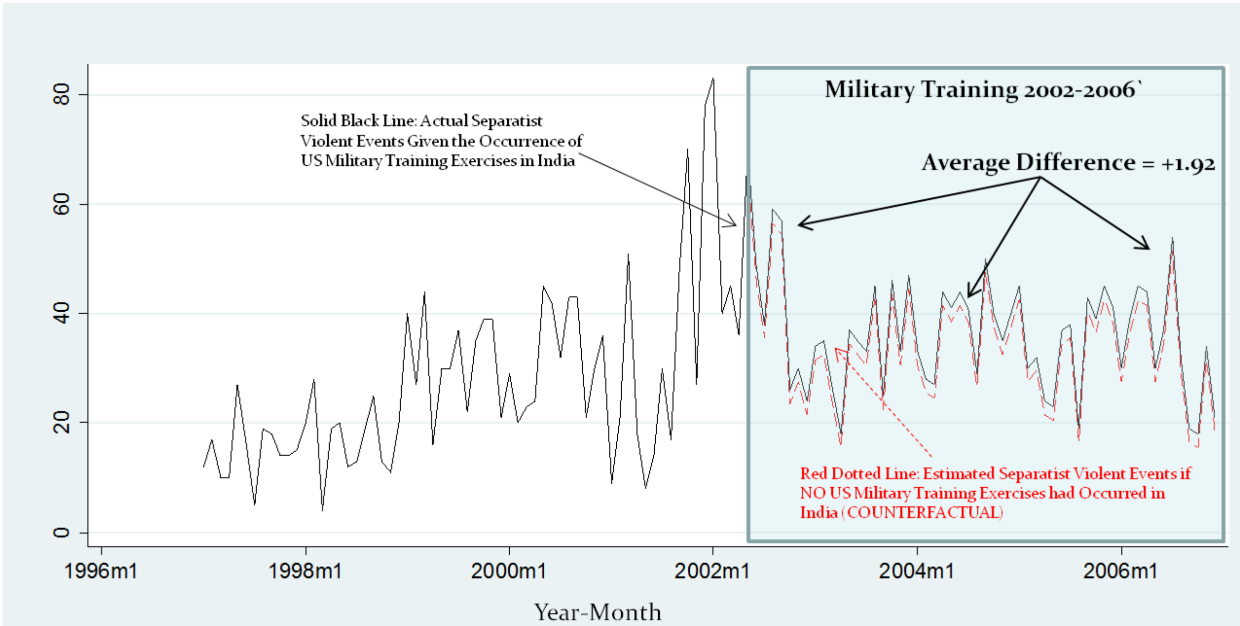

Figure 4 The Counterfactual Series (red-dotted) Overlaid on the Actual Series (black-solid)

In addition to the counterfactual analysis, we also performed an impact assessment analysis. The coefficients from the models are displayed in Table 2. In short, we added a dummy variable coded 1 under military training and 0 under no military training to our model and estimated its effect. We found that on average, military training increases attacks by about 2.56. Our impact assessment finding is consistent with our counterfactual finding adding credence to our results.

Table 2 Negative Binomial Impact Assessment Results for Military Training on Separatist Violence, India 1997-2006

Model 1: Constant Effect				Model 2: Curvilinear Effect		
Independent Variable	*Coef.*	*SE*	*Sig?*	*Coef.*	*SE*	*Sig?*
Training Dummy (Average Constant Effect)	**0.0875**	0.0445	95% level	**0.0010**	0.0000	Not Sig
Training Counter				**0.0088**	0.0045	95% level
Training Counter Squared				**-0.0002**	0.0001	94% level
Societal Sentiment towards Dissidents	**0.0118**	0.0075	90% level	**0.0124**	0.0075	90% level
Societal Sentiment towards Government	**-0.0118**	0.0085	85% level	**-0.0148**	0.0089	90% level
Separatists Low-Level Cooperation	0.0087	0.0030	99% level	0.0088	0.0031	90% level
Separatists Medium Level Cooperation	-0.0292	0.0143	95% level	-0.0320	0.0145	97% level
Separatists Low-Level Hostility	0.0097	0.0032	99% level	0.0105	0.0033	99% level
Separatists Medium-Level Hostility	0.0180	0.0050	99% level	0.0181	0.0051	99% level
Government Hostility (all scaled)	-0.0022	0.0003	99% level	-0.0022	0.0003	99% level
Constant	2.3547	0.0778	99% level	2.3559	0.0771	99% level

That said, we also wanted to know if there was a dynamic temporal relationship. That is, while on average military training might increase attacks by about 2 per month, was this effect in fact constant across the period or did it vary with respect to the duration of military training. We specified a model that would allow us to test these hypotheses by adding a duration variable to the model and testing its functional relationship to separatist attacks. Figure 5A shows the average change in attacks over time during the military training period. As one can see from the graph, military training increased attacks in the short-run and decreased attacks in the long run. In fact, there were fewer attacks at the end of 2006 than there were in 2002 when training. We need to also perform such an analysis with the counterfactual method to see if our finding is further supported by examining the month to month differences in the counter-factual and actual series. We believe we would find supporting evidence. We conclude that while training may increase attacks on average over the period, the frequency of violent attacks was less at the end of the training than it was at the beginning. We would argue that military training is an overall success and that staying the course ultimately provides greater long-term benefits.

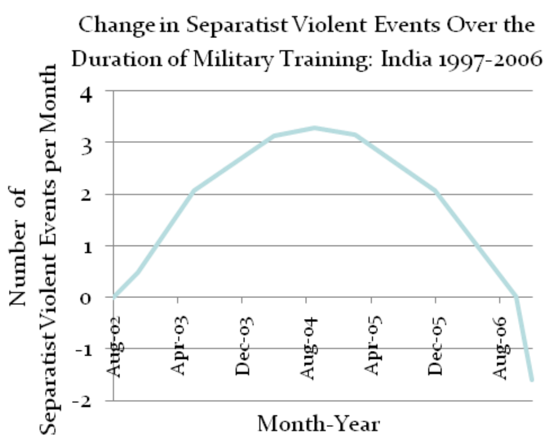

Figure 5A

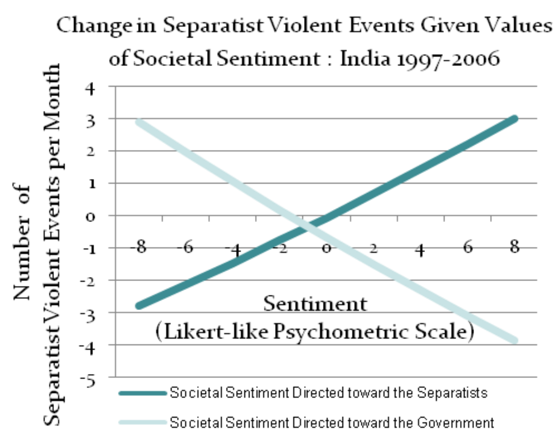

Figure 5B

Moreover, we also wanted to discuss some findings with respect to our sentiment. Figure 5B reports our findings. Our results show that as sentiment towards the separatists becomes more positive the number of separatists' attacks increase. In contrast, as sentiment towards the host government increases, separatist attacks decrease. While many authors have argued that this should be the case, there is not much empirical evidence for the argument. We think our results are important in understanding the ebb and flow of societal sentiment and how such sentiment affects violence on the ground. Given the attention that the U.S. government and U.S. military COIN manuals shed on winning over the populace we feel we have the capabilities to understand the effects of various U.S. actions on such sentiment and indirectly on the intensity of political violence. All in all, we have the capabilities to begin understanding the dynamic relationship we posited in Figure 1 above. Which U.S. actions win the support of the people and how does such support affect the intensity of conflict? These questions are at the heart of future studies.

Finally, note that we could take our model a bit further examining the direct and indirect effects of military training on various separatist and host nation activities. For example, we might find that U.S. military training positively affects societal sentiment towards the separatists and that as societal sentiment increases towards separatists, separatists are more likely to increase the number of violent attacks and decrease their nonviolent activities. So U.S. military training might have a direct positive effect on separatists high hostility (violence) and a positive indirect effect through societal sentiment. In sum, the total effect of military training on separatist violent activities is greater than the direct effect by itself. It is important to trace these effects and understand which variables amplify relationships and which variables dampen effects. Some effects can be cancelled out while others can be strengthened when examining complex direct and indirect effects. This is also the subject of forthcoming papers.

7.0 Positive U.S. Diplomatic Actions & Military Actions in the Philippines

In the second analysis we examined the effects of positive U.S. diplomatic actions and high-level military actions on separatist violence in the Philippines (1997-2006). Separatist violence was measured by events such as armed clashes with government forces, the use of unconventional violence such as car bombings and suicide attacks, and abductions and hostage takings. Our treatment variables were U.S. high-level positive diplomatic actions and high-level military actions. Diplomacy was operationalized using the following event types: signings of major agreements such as the agreement to cooperate on the

War on Terror and promotions of investment by U.S. companies such as Exxon Mobile, military cooperation with the Philippines government such as training exercises, and the sharing of intelligence information with the Philippines. We operationalized military actions by the mobilization of forces, moving fleets into strategic positions, imposing blockades and restrictions of movement, military training and joint forces exercises, and assassinations of terrorist leaders.

Figure 6 highlights the periods of U.S. diplomatic and military actions across the time-series of separatist violence in the Philippines. The green shading highlights diplomatic actions, the yellow highlights military actions, and the purple indicates that both were present.

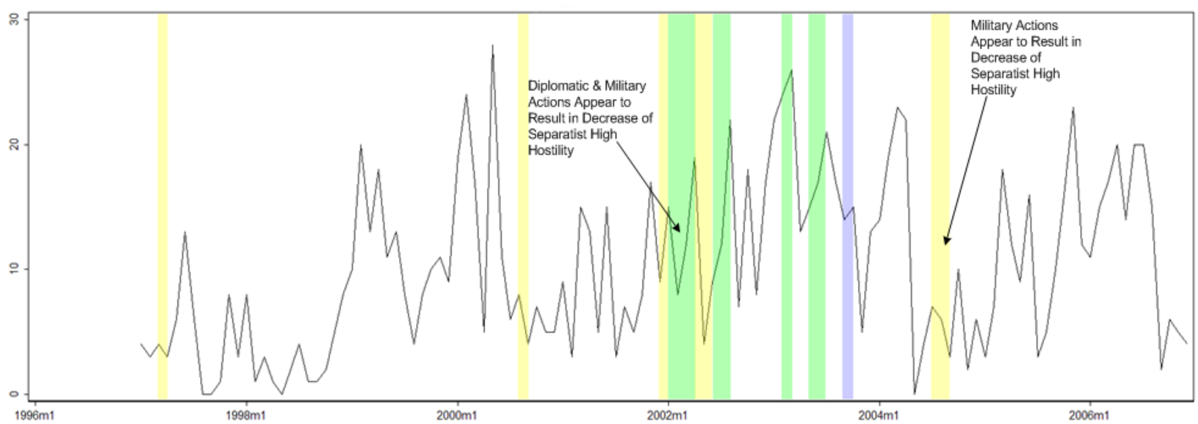

Figure 6 Separatist Violent Events Philippines (1997-2006) with Highlighted Periods of U.S. Diplomacy and Military Actions

Again, the genetic algorithm we employed proved to provide the most percentage increase in the balance across the cases. The overall percent balance improvement score (i.e., distance) improved upwards of 98% indicating that the cases were well matched. See Table 3 for balance statistics across a couple matching procedures.

Table 3 Percent Balance Improvement Between Treated and Control Groups for Philippine Diplomacy Model*

	Full Matching	Genetic Matching
distance	98.16	98.66
separatistsAlllowcoopct	96.48	99.77
separatistsAllmedcoopct	91.28	97.68
separatistsAlllowhostilityct	71.25	92.29
separatistsAllmedhostilityct	81.35	90.8
Gseparatistshosttotals	89.64	87.45

*Selected input variables

Again, the modeling strategy assumes and factors in error associated with the matching procedure. Once we had the cases matched, we ran the model on the untreated cases and generated our counterfactual series, we then took the average difference to compute the effect of high-level positive diplomatic actions. Figure 7 shows the counterfactual series (dotted red line) overlaid on the actual series of separatist violence events (grey solid line). The figure highlights a 4.2 difference in attacks during the high-level diplomatic actions periods. That is, U.S. positive diplomacy in the Philippines reduced separatist violent events (controlling for other factors) by about 4 violent events per month. Four fewer violent events would have transpired per month if U.S. diplomacy had occurred during those times. The effect is statistically significant at the 95% level.

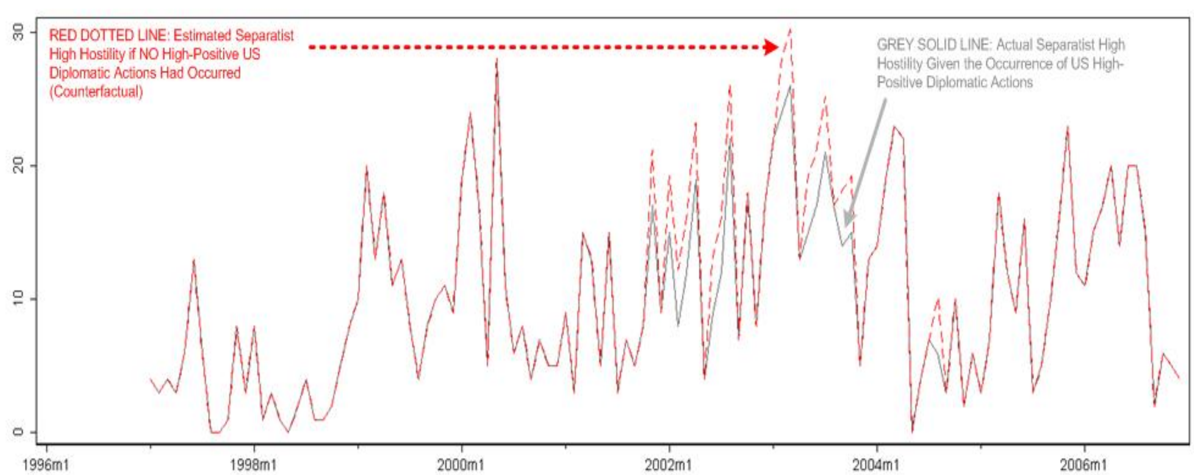

Figure 7 Average Effects of High-Level U.S. High-Level Positive Diplomatic Actions on Separatist Violent Events: Philippines 1997-2006

We proceeded in much the same way for military actions. Figure 8 shows the counterfactual series (dotted red line) overlaid on the actual series of separatist violent events (grey solid line). The figure depicts a 5.88 difference in attacks during the high-level military actions periods. That is, U.S. military actions defined and operationalized above in the Philippines reduced separatist violent events (controlling for other factors) by almost six violent events per month. The effect is statistically significant at the 95% level.

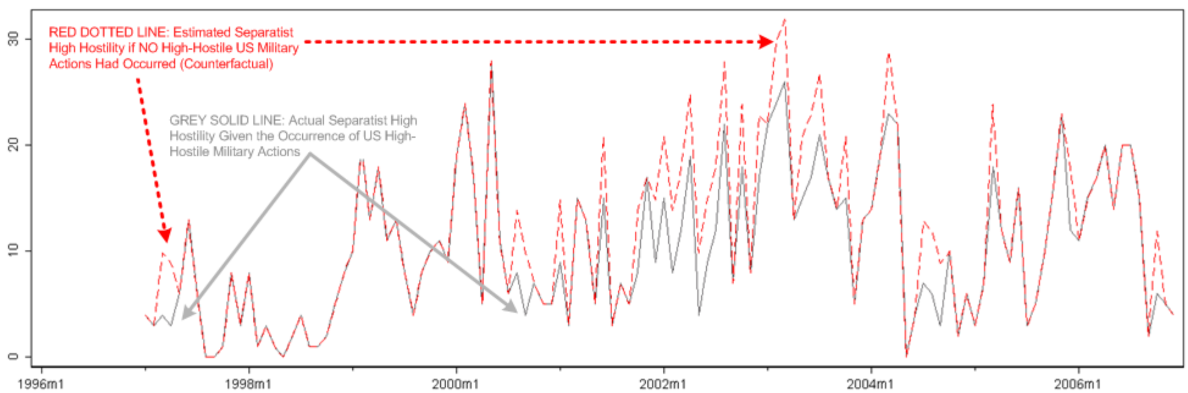

Figure 8 Average Effects of High-Level U.S. High-Level Military Actions on Separatist Violent Events: Philippines 1997-2006

In much the same way as we performed a complimentary time-series impact assessment of India military training, we designed and implemented an impact assessment of two joint U.S.-Philippines military exercises in the Philippines. Figure 9 illustrates the two main U.S.-Philippines exercises overlaid on the violent separatist series. While much of these exercises consisted of joint training exercises, there were joint missions such as hunting down and killing terrorist leaders and armed skirmishes among U.S.-Philippines troops and militant groups such as Abu Sayyaf. In fact, Balikatan ("Shoulder to Shoulder" in Tagalog is an annual joint training exercise) 02-01 in 2002 was the largest U.S. military deployment engaged in actual combat against "real actual targets" on Philippine soil since the Philippine-American War. The explicit mission of the exercise was to eliminate the Abu Sayyaf and bring social stability to the region. The ultimate goal of exercise was to recover two U.S. missionaries held captive by Abu Sayyaf. At the same time, the U.S. & Philippines signed a series of bilateral agreements that stipulated U.S.

diplomatic actions. The U.S. military engaged in a series of civil military projects to help improve dilapidated infrastructure while also upgrading the transportation capacity of the island. Moreover, the U.S. military became involved in constructing a circumferential road, water, an airstrip, a port, and bridges. Finally, U.S. troops also engaged in volunteer activities such as painting walls, building canteens, and renovating school houses.

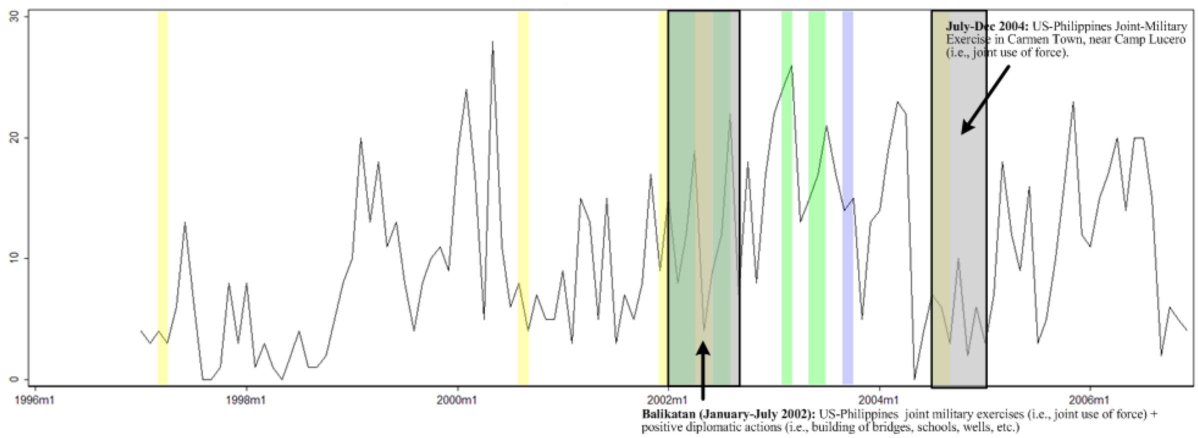

Figure 9 Separatist Violent Events Philippines (1997-2006) with Highlighted Periods of joint U.S.-Philippines Military Actions

To model the impacts of such exercises, we coded the presence (1) and absence (0) of Balikatan & Carmen Town Exercises by dates of operation activities. We then specified a model to estimate the impacts of Balikatan and Carmen Town activities in the presence of control variables (e.g., other DIME actions, other day to day Philippine government activities, etc.). We estimated the impacts via an Autoregressive Integrated Moving Average (ARIMA) time-series model and a Zero-Inflated Negative Binomial (ZINB) model. The results were consistent across both estimators. Table 4 displays those results. In short, the ARIMA results conclude that the exercises reduced attacks by about 4.6 a month, while the ZINB results showed that attacks were reduced by 3.3 a month. At the end of the day, both methods find that such activities reduced separatist violence. The results produced using the impact assessment methods are similar and corroborate those results from the matched case analysis. Two separate analyses using different methods and operationalized variables conclude that high-level U.S.

military and high-level U.S. diplomatic actions reduced the frequency of violent attacks by separatists in the Philippines.

Table 4 Time-Series Impact Assessments for U.S.-Philippines Joint Military Exercises: ARIMA and ZINB Results

	ARMA Results				ZINB Results (2 Equations: one estimates probability of 0; other estimates given non-probability of zero the number of events)			
	Coef.	*Std. Err.*	*z*	*P>z*	*Coef.*	*Std. Err.*	*z*	*P>z*
Government Hostility	0.1256502	0.0239657	5.24	0	0.0174585	0.002139	8.16	0
Government Hostility Squared	-0.000145	0.0001527	-0.95	0.342	-0.0000441	9.02E-06	-4.89	0
Government Hostility towards to Social-Religious Actors	0.1004553	0.3619167	0.28	0.781	0.0353752	0.0382818	0.92	0.355
US Positive Diplomacy towards Philippines	0.0001676	0.0031437	0.05	0.957	0.0000331	0.0005618	0.06	0.953
US Negative Diplomacy towards Philippines	-0.0010821	0.0155791	-0.07	0.945	-0.0004629	0.0038102	-0.12	0.903
US Positive Information towards Philippines	-0.0389551	0.0307229	-1.27	0.205	-0.0011331	0.0055331	-0.2	0.838
US Negative Information towards Philippines	0.0187743	0.0104183	1.8	0.072	0.0022156	0.0016147	1.37	0.17
US Positive Military Actions towards Philippines	0.0113088	0.0093126	1.21	0.225	0.0007651	0.0022005	0.35	0.728
US Negative Military Actions towards Philippines	0.0087394	0.0084809	1.03	0.303	0.0002673	0.0008803	0.3	0.761
US Positive Economic Actions towards Philippines	0.0113552	0.0222792	0.51	0.61	-0.0005082	0.0017357	-0.29	0.77
US Negative Economic Actions towards Philippines	-0.0204173	0.4213662	-0.05	0.961	-0.0041683	0.0201403	-0.21	0.836
Balikastan & Carmen Town Operations	**-4.606471**	**1.619293**	**-2.84**	**0.004**	**-0.445081**	**0.2247764**	**-1.98**	**0.048**
Time Counter	0.0347928	0.0105568	3.3	0.001	0.0041001	0.0026998	1.52	0.129
Constant	0.5668321	1.228198	0.46	0.644	1.05125	0.3097961	3.39	0.001
ar (1)	0.9681103	0.0460639	21.02	0				
ma (1)	-0.8946668	0.0825438	-10.84	0				
Probability of Zero Events								
Government Hostility					-5.602265	0.3058745	-18.32	0
Government Hostility Squared					0.0284686	0.0014744	19.31	0
Government Hostility towards to Social-Religious Actors					53.50289	1.836913	29.13	0
US Positive Diplomacy towards Philippines					-0.8772602	0.0420951	-20.84	0
US Negative Diplomacy towards Philippines					0.9059524	0.0479286	18.9	0
US Positive Information towards Philippines					0.7355866	0.0419279	17.54	0
US Negative Information towards Philippines					1.032614	0.0328036	31.48	0
US Positive Military Actions towards Philippines					1.632993	0.0780213	20.93	0
US Negative Military Actions towards Philippines					-1.214069	0.0302646	-40.12	0
US Positive Economic Actions towards Philippines					-0.0590336	0.0677343	-0.87	0.383
US Negative Economic Actions towards Philippines					-10.77825	0.3982962	-27.06	0
Balikastan & Carmen Town Operations					203.4462	7.562617	26.9	0
Time Counter					-2.436093	0.1587457	-15.35	0
Constant					42.78076	1.559964	27.42	0

8.0 Conclusion

Do U.S. counter-insurgency DIME actions reduce political conflict in a region or feed the fire? Which policy strategy offers optimal results? Using the latest counterfactual research methodologies, we are able to evaluate the direction and magnitude of different policy strategies aimed at reducing overall levels of violent political conflict within an area of operation. The multi-method approach employed above offers confirmatory evidence and lends credibility to our results.

We found differing and even directly opposite results across different countries. On an aggregate level hands-on military training and cooperation increased separatist violence in India but quelled it in the Philippines. This is not surprising, given that our study treated countries heterogeneously and respected the different contexts which shape the political spectrum in each. Under varying circumstances Indian separatists saw fit to fight back whereas the Filipino MILF and Abu Sayyaf groups chose to lay low. These disparate findings strengthen, rather than undermine our results.

Just as physicians treat a cancer with differing prescriptions for different patients, decision makers must be aware that not all tools are equally well-suited to all operational environments. Directly supporting the Armed Forces of the Philippines may work wonders in Mindanao, but identical operations in Indonesia or Bangladesh may yield little gain or worse yet, they may further destabilize security. The analysis we have undertaken here can offer a framework for supporting such difficult and open-ended choices.

We used multiple methods to internally validate our findings. Matched case counterfactual analysis allowed us to see "what would have happened if" while still comparing apples to apples. At the same time, we employed multiple interrupted time series techniques to answer the question "what effect will action X cause on the dependent variable?" In our study, both methods gave broadly similar results while also offering different nuances. In the Indian case time series impact analysis showed that while military training increased separatist violence on the whole, it achieved its intended effect, reducing violence in the long run.

We must admit, however, that the same attributes of this study that we champion may be construed as weaknesses. The results presented here are country-specific and as such are not readily generalizable. Findings from India do not directly translate to subsequent areas of operation. Individual studies would have to be conducted on any country requiring US intervention. One possible way forward is to match observations across countries rather than solely within. Such an approach may lead to more generalizable results. Despite these limitations our results indicate a nascent path forward as research begins focusing on the impacts of specific DIME actions.

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