A Bayesian Time Series Approach to the Comparison of Conflict Dynamics*

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Abstract

Despite the apparent decline in interstate war and some other kinds of conflicts since the middle of the last century, the world continues to be plagued by lethal, politically motivated violence. We address major deficiencies in the rationalist accounts of this violence. Using time series data from the Event Data Project (EDP) at Pennsylvania State University and a Markov-switching, Bayesian multivariate time series model, we produce novel tests of rationalists' theoretical expectations and of empiricists’ stylized facts.

We show that there are significant differences in the dynamic structure (mechanisms) of conflicts in the Levant, Cross Straits, and Indian subcontinent. In particular, the number of conflict phases and the lag structures of these conflicts are not the same. Moreover the regimes in the Levant are best conceived in terms of different variances while those in the other two cases in terms of different intercepts. These differences translate into different short and long term patterns of (non) reciprocity and of conflict phase shifts. Hence the evolutionary—non-equilibrating—behaviors of the belligerents in the three conflicts are distinct (Diehl, 2006). The actual patterns are different than those reported recently by Zeitoff (2011) for the Levant but they appear consistent with some commentaries on Pakistani policymaking (Tremblay and Schofield, 2005). There is little evidence that succession processes or changes in the type of government are the source of conflict phase shifts. The exception is the change in the regime type of Pakistan in the late 1990s; this change does appear to have caused a conflict phase shift. Empirically, conflict dynamics across rivalries differ greatly. There are major differences in the patterns of verbal and material behavior in the Cross Straits and Indian Subcontinent as well as between the conflict dynamics in these two rivalries and the conflict dynamics between the the Israelis and Palestinians. As regards the idea of conflict phase shifts, we find, contrary to many works in the literature, that there are a relatively small number (2-3) in each of our cases. The propensity of some scholars to find 4 or more phases seems to be due to post hoc pattern hunting of the kind that Taleb (2010) and others criticize.
1 Introduction

The world continues to be plagued by lethal, politically-motivated violence. Despite the apparent decline in interstate war since the middle of the last century, according to the Geneva Declaration on Armed Violence and Development, since 2004, more than 50,000 people have died violently annually as a result of political conflict; 55,000 people are estimated to have died due to political conflict in 2011.¹ There remains, in many parts of the globe, the potential for more even more lethal armed conflicts. For example, less than four years ago, Israel invaded Gaza and more than a 1000 Palestinians lost their lives. Today, Israel and Hamas regularly shoot rockets into each others’ territory causing death and destruction. In South Asia, India and Pakistan continue to enlarge their nuclear arsenals and to argue over control of Kashmir. Meanwhile, in East Asia, the possibility of a cross straits conflict continues to motivate P.R.C. military planning. The P.R.C. still has about 1600 missiles aimed at Taiwan. And Taiwan plans an almost 8% increase in its military budget, most of which is dedicated to the development of a cruise missile, a supersonic ship to ship missile, and an upgrade on its domestically produced defense fighter.²

The literature on armed conflict is voluminous. It attributes conflict to a variety of factors: the rational calculi of belligerents, asymmetric information held by elites versus mass publics, the grievances associated with enduring (strategic) rivalries, the interest group politics deriving from levels and particular mixes of trade, the workings of democratic versus authoritarian government and of nonpersonalist versus personalist authoritarian regimes, the impacts of insurgency, and transitions to democracy. Certain stylized facts motivate much of this research. Examples are the frequent observation of behavioral phase shifts as conflicts escalate and then deescalate, and the destabilizing effects of political successions on inter and intra state relations. Investigators try to identify the “recurring mechanisms” that produce conflict and explain the stylized facts (McAdam et al., 2001, xvi, 12-13). Understanding these mechanisms supposedly is the key to explaining the different action-reaction sequences that characterize (non)rivalry in particular (Colaresi et al., 2007, 14, 19) and the similarities and differences between conflicts like we continue to observe between Israel and the Palestinians, India and Pakistan, and China and Taiwan in general.

Unfortunately, much of this research is seriously deficient. First, most of it is highly static. Many of the explanations produced by conflict theorists tell us how a single conflict occurs but not how the outcome of one conflict sows the seeds of the next conflict, let alone how the conflict ebbs and flows in short periods of time. The frequent focus on discrete “conflict onsets” or “dispute initiations” in the rivalry and comparative authoritarianism genres, respectively, are illustrative; each onset is treated as a single independent event not

¹The report of the Geneva Declaration on Armed Violence and Development distinguishes (a) collective versus individualized and (b) conflict (politically motivated) versus criminal (economically motivated) violence. It is cited in the opening of Isaac’s introductory essay to a Symposium on the Study of Violence in the Perspectives on Politics (2012). Also cited by Isaac is Pinker’s new book, The Better Angels of Our Nature (2011). Pinker argues that “we may be living in the most peaceable era in our species’ existence” (Pinker, 2011, xxi). This is not the place to critique Pinker. Suffice it to say that, among other things, while he makes passing reference to the lives of turkeys and repeatedly acknowledges the pitfalls of “hallucinat[ing] grand patterns” and “extrapolat[ing] from them in to the future” (ibid. 191, 193), Pinker actually never engages the Taleb (2010) argument about the occurrence of “black swans.”

²From Nexon blog.
just in space but also in time. A simplistic, usually one-way notion of causality is a second major deficiency. Conflict is explained in terms of a single linear additive relationship; there is little provision for feedback and (or) endogeneity.\(^3\)

The lack of progress in understanding the similarities and differences in conflict dynamics is due, in part, to some serious methodological difficulties. Up until now, our data have been sparse and highly temporally aggregated.\(^4\) We also did not have models which could analyze the complexity in conflict dynamics, for instance, capture conflict phase transitions and the interconnected directed behaviors of belligerents simultaneously.

This paper addresses the major deficiencies in the study of conflict, especially in the rationalist literature on conflict dynamics. We extract from this literature its key theoretical expectations and stylized facts. Then, using time series from the Event Data Project (EDP) at Pennsylvania State University and a Markov-switching, Bayesian multivariate time series model, we produce a novel test of these expectations and facts. We show that there are significant differences in the dynamic structure (mechanisms) of conflicts in the Levant, Cross Straits, and Indian subcontinent. In particular, the number of conflict phases and the lag structures of these conflicts are not the same. Moreover the regimes in the Levant are best conceived in terms of different variances while those in the other two cases in terms of different intercepts. These differences translate into different short and long term patterns of (non) reciprocity and of conflict phase shifts. Hence the evolutionary–non equilibrating–behaviors of the belligerents in the three conflicts are distinct (Diehl, 2006). The actual patterns are different than those reported recently by Zeitzoff (2011) for the Levant but they appear consistent with some commentaries on Pakistani policymaking (Tremblay and Schofield, 2005). There is little evidence that succession processes or changes in the type of government are the source of conflict phase shifts. The exception is the change in the regime type of Pakistan in the late 1990s; this change does appear to have caused a conflict phase shift. Empirically, conflict dynamics across rivalries differ greatly. There are major differences in the patterns of verbal and material behavior in the Cross Straits and Indian subcontinent as well as between the conflict dynamics in these two rivalries and the conflict dynamics between the the Israelis and Palestinians. As regards the idea of conflict phase shifts, we find, contrary to many works in the literature, that there are a relatively small number (2-3) in each of our cases. The propensity of some scholars to find 4 or more phases seems to be due to post hoc pattern hunting of the kind that Taleb (2010) and others criticize.

Our investigation is divided into three parts. Part One reviews and synthesizes the rationalist literature. Our research design is presented Part Two. Our results are presented in Part Three. The Conclusion summarizes the findings and outlines some directions for future research on conflict dynamics.

\(^3\) An example is the one-way causal schematic in McAdam et al. (2001, Figure 10.3, 333). An exception here is the newer work on trade and conflict. It uses tools like the CDSIMEQ estimator to analyze the simultaneity in the trade-conflict relationship (Keshk et al., 2004; Li and Reuveny, 2011).

\(^4\) On this shortcoming of the literature see the criticisms in Brandt et al. (2011) and Zeitzoff (2011). The MIDs data set is an example. Such measures mask causal relationships and dynamics. In addition, up until now we had no technology to analyze what are nonlinear simultaneous systems of behavior of moderate scale (systems with multiple actors). We also use collections of ad hoc dummy variables to represent behavioral shifts. These dummy variables may overfit the data. Even when based on tests for structural instability, dummies imply permanent shifts in behavior when, in fact, such shifts may recur as in sequences of conflict escalation and deescalation.
2 Theory and Stylized Facts

2.1 Rationalist Theories of Conflict

2.1.1 One-level theories

The rationalist explanation argues that war is costly ex post and there almost always is, ex ante, the possibility of a negotiated settlement between the belligerents. This negotiated settlement will make the belligerents better off than fighting a war. Wars occur nonetheless because of 1) belligerents’ possession of and incentives to misrepresent their private information, 2) the lack of commitment mechanisms to enforce negotiated settlements and 3) the indivisibility of contentious issues. These problems supposedly exist even if the belligerents interact over time. To be more specific, even if reciprocity develops between adversaries, negotiated settlements of conflicts are unattainable (Fearon, 1995, esp., 405).

Consider the Taiwan Straits conflict (which we refer to as the Cross-Straits). Despite several serious crises, no war has broken out between China and Taiwan. Hence, it appears the three problems have been solved. For instance, Ross (2000) and others stress the effectiveness of the signaling that went on between these governments in the 1995-1996 crisis. There even is evidence that the Chinese met with U.S. officials several times in Beijing in both February and March 1996, assuring them privately that China would not attack Taiwan (Tung, 2003, 157). As regards the need for a commitment mechanism, much writing on the Cross Straits suggests that the U.S. helps enforce tacit and explicit agreements between the Chinese and Taiwanese. The American policy of “dual deterrence” is illustrative.\(^5\) Also suggestive is the argument that the U.S. helps enforce agreements by acting as a “pivot” or balancer in the conflict (Wu, 2005). There is evidence of triangularity in Cross Strait behavior, cases in which one government asked another government to discipline a third

\(^5\)Dual deterrence is the U.S. policy of simultaneously discouraging Beijing from taking military action and convincing Taiwan not to declare independence (Bush, 2005, esp. 13).
government and (or) designed its policies toward its adversary and the U.S. jointly. Finally, as Lin (2000) has shown, the Taiwan straits issue is divisible. There is a range of options in this case between unification of China and Taiwan and outright independence of Taiwan. Illustrative is the Chinese policy of “One country, two systems.”

The history of the India-Pakistan conflict is quite different. Because of its regime type (see below) the Pakistani governments “either ignore or misinterpret international signals that worsen the consequences of . . . disputes” (Tremblay and Schofield, 2005, 237). Basrur (2010, 15) contends that the Pakistanis are more adept at signaling when it comes to nuclear testing. But, in terms of conventional negotiations, the run-up to the Kargil War of 1999—the contrast between the Lahore agreement and failed meeting at Agra—suggests that they continue to be unable and (or) unwilling to signal their intentions accurately (Ganguly, 2001, chapter 6). Although the two countries agreed to cease fires several times, India and Pakistan frequently have resisted mediation efforts by the U.N. and the great powers. Finally, in contrast to the Cross Straits case, the Jammu-Kashmir dispute appears to be indivisible. Analysts agree that Pakistan’s irredentist aims can only be met when all Muslim people in this territory are under its rule; India views any agreement that dismembers Jammu-Kashmir as antithetical to its national interests (Paul, 2005; Ganguly, 2001).

The dynamic version of the rationalist account stresses the idea of reciprocity. Building on the seminal work of Axelrod (1984) and research on human behavior in repeated non-zero-sum games, scholars found that cooperative behavior by one agent often begets cooperation by another. Moreover, this cooperative behavior is rational if the “shadow of the future” (expected length of play) is sufficiently long. The prevalence of these so-called tit-for-tat strategies have been uncovered in superpower (Cold War) relations (Goldstein and Freeman, 1990), in Indian-Pakistani relations (Ward, 1982), in the Middle East (Goldstein et al., 2001), and in the Balkans (Goldstein and Pevehouse, 1997). Scholars uncovered reciprocal behavior in subnational cases as well (Moore, 1998; Shellman et al., 2007). Contrary to Fearon’s (1995) argument, cooperation does appear to evolve without commitment mechanisms. Illustrative is the success in achieving arms control without agreements between the Superpowers.

Up until recently, however, dynamic, rationalist theories suffered from some serious flaws. For example, there is much evidence that the propensity to initiate cooperation and to reciprocate varies across groups (Ward 1982). For instance, Israeli leaders have complained explicitly about a lack of reciprocity on the part of Hamas and Islamic Jihad (Morris 1999: 645). In fact, Brandt et al. (2008, 360) recently found inverse rather than reciprocal behavior on the part of the Palestinians in the period April 1996-March 2005. And Zeitoff (2011) found much evidence of “asymmetric response dynamics” during the Gaza conflict: Israel responded strongly in kind to conflict from Hamas but Hamas did not exhibit any statistically

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On the concept of triangularity in regional and world politics see Goldstein and Freeman (1990). A discussion of the statistical challenges triangularity poses can be found in Brandt et al. (2008). On triangularity in the cross-straits see, for instance, Chu (1997, 253) who explains how Taiwanese policies toward the Chinese and the U.S. were related. See also (Wu, 2005, 56-57) and (Tung, 2003, 156-7) on how, in 2000, the Chinese asked the U.S. to pressure the Taiwanese not to declare independence.

Lin (2000, Table 1) represents five possibilities regarding Taiwan’s international status on a [0,1] continuum ranging from a value of 0: Taiwan is an ordinary province of the P.R.C. to a value of 1: Taiwan is an independent country.

Note that Fearon’s (1995) claims about reciprocity and dynamics are assertions. His rational choice analysis is static in nature; he never performs any dynamic, rational choice analysis.
significant responses to shocks in conflict from Israel.

One reason for a lack of reciprocity is that leaders try to manipulate or respond to their constituents’s preference for conflict or cooperation (De Mesquita et al., 2003). This brings us to the two-level version of rationalist theory.

2.1.2 Two-level theories

This second major body of rationalist theory analyzes the connection between policy and domestic politics. One strain stresses information (a)symmetry between elites and mass publics. When asymmetries exist, leaders can try to “outbid” their opponents, convincing the public that they are hawkish and their domestic rivals are dovish. This can lead to conflict escalation (Colaresi, 2005). In another strain, elites and mass publics essentially have the same information. Publics then can impose audience costs on leaders and, in turn, bolster the credibility of their government’s policies. For example, domestic audiences can punish leaders for backing down from their threats (Fearon, 1994) and for defecting from cooperation (Guisinger and Smith, 2002; McGillivray and Smith, 2000). Because, under some conditions, an opponent can observe such constraints, the threats of a government become more credible when the possibility of domestic punishment exists. Until recently it was assumed that these domestic constraints applied only in democracies. But, Weeks (2008, 2012) shows that they apply in some autocracies as well, namely, those where elites can coordinate punishment of leaders, outsiders can observe these punishments, and the ruling elites also prefer not to see their leader back down from a threat. Only personalist regimes, certain types of monarchies, and young democracies lack these conditions, Weeks argues.\textsuperscript{9}

This two-level theory is well-supported in the historical record. Colaresi (2005) shows how these two level forces help explain Israeli-Egyptian relations from 1949-1979. Anecdotal evidence from the Levant also supports it. Illustrative is the fact that Israel’s Yitzhak Rabin commissioned polls apparently to learn how to best establish credibility at a crucial juncture in the negotiation of the Oslo Accords (Auerbach and Greenbaum, 2000). Again, Brandt et al. (2008) found that a model with causal linkages between Jewish public opinion and Israeli-Palestinian (and U.S.) behavior not only better fit the event data but also forecast ex post better than a model without Jewish public opinion. They also found that over time in the Levant, public opinion acted as a negative feedback mechanism—Jewish public opinion in Israel prevented all-out war with the Palestinians, but it also slowed the movement toward peace.

The two level rationalist account also appears to apply to the cross-strait case. China is the single party state—that has “visible coordination” (Weeks, 2008, 46). The work of such scholars as Shih (2008) and his co-authors (Shih et al., 2010) on elite bargains in China show this. As explained below, Taiwan, in its early stages of democra-

\textsuperscript{9}Weeks (2012) most recent work distinguishes four types of autocracies: personalist/nonpersonalist x civilian/military audience. She finds that personalist regimes have no effective audience costs. And, civilian regimes with powerful elite audiences are no more belligerent than democracies.
Students of the India-Pakistan conflict agree that the opinions of “attentive publics” affect governments’ behaviors. Ganguly (2001, 7-8) argues that the associated audience costs play a much larger role in India than in Pakistan. In his view, public opposition to compromise in the Jammu-Kashmir dispute is a major constraint on Indian governments; there is no domestic group in India that favors surrender of Muslim populated lands in Kashmir. But, he also alludes to attentive publics in Pakistan (ibid. 136). Basrur (2010, 22) argues that “outbidding” remains common in both countries.

2.1.3 Destabilizing Short and Medium-Term Forces

Several forces that can cause deviations from the expectations of the two-level theories. For instance, changes in political regime type can alter the dynamics of the two-level game. The idea is that these changes cause agents to repeatedly revise their strategies. This, in turn, causes changes in the coefficients of the equations that describe their behaviors. Failing to account for these coefficient changes could produce incorrect causal inferences.

*Political Succession:* It is generally agreed that succession can destabilize conflict dynamics. In elections, contestants send signals as they try to win votes. Candidates promise foreign policies that may require new bargains between belligerents. If new leaders are elected, there can be even more uncertainty about future policies and hence the viability of existing agreements. Consequently belligerents may revise their strategies during these periods changing the behavioral dynamics of the conflict system. In the case of the Gaza conflict, for example, there is evidence that Kadima invaded, in part, to demonstrate its resolve in the run up to its election against the Likud party.\[11\]

The destabilizing effects of public opinion and elections are evident in the Cross Straits and Levant cases. Kuan (2007) and Kuan and Lin (2007) stress that in the run-up to Taiwanese elections, the rhetoric of candidates and parties signal that major changes in policies are possible. Ross (2000, fn. 106, p.123) argues that in 1996, incumbent President Lee Teng-hui encouraged destabilizing changes in Taiwanese public opinion. Study of this and other elections lead observers like Saunders (2005, 974); see also Wu (2005, 60) to argue that the Taiwanese Presidential election system is a major source of instability in Cross Straits’ dynamics. This is consistent with Lin’s (2000:10) argument that certain proposals made by one country can destabilize cross-strait relations. A more complex pattern of behavior is seen in the Levant. There is evidence of electorally motivated, strategic violence by Hamas and Islamic Jihad: violent actions were taken toward Israelis in an attempt to tarnish the image of the Labour party and to unseat it (Morris, 1999, 636-7).

Succession is the source of much uncertainty in India and Pakistan. Since 1989 elections have produced coalition governments in India. The formation and policies of these coalitions is harder to predict than in plurality electoral system. Pakistan has experienced repeated

\[10\] An example of the application of the concept of two level games to cross-strait relations is Clark (2006); see also Chan (2010, 6ff). Lin (2000, 12) argues that the two-level game concept employed in most works in international relations is not applicable here because the cross-strait case is essentially a zero-sum game in which the winsets of China and Taiwan do not overlap.

\[11\] Of course, Hamas enjoyed more autonomy in the Palestinian movement itself by virtue of its 2006 electoral victory over Fatah. On both points see Zeitzoff (2011, 941).
shifts between civilian and military control (see Appendix). This history, when combined with its governments ineptitude at signaling and propensity for outbidding, makes it even more difficult to negotiate with the Pakistanis.

Nondemocratic regimes also have succession processes. Consider, again the Taiwan straits. For the last half of the twentieth century, Weeks (2012) codes the P.R.C. as a single party autocracy. This is because the P.R.C. has visible coordination among elites and hence, in this sense, audience costs constrain the Chinese government and enhance the credibility of its policies. But stability in cross-strait dynamics depends on political equilibrium with China’s autocracy–dominance by one or a balance of power between rival elite faction(s). The lianghui–meetings of National People’s Congress (NPC) and of the Chinese People’s Consultative Conference(CPPCC)–are the venues which signal the stability of and changes in this equilibrium. In fact, Wu (2005, 59) argues that the party congress is essentially the equivalent of Presidential elections in the U.S. and the R.O.C. While they equivocate about whether the lianghu operate as “selectorates,” Shih et al. (2010) develop an indicator that shows how the relative share of ties between Party Secretaries and Central Committee members tracks elite (factional) power in China. This indicator shows that there recurring power shifts some of which are precursors to leader succession. An example is the increase in the share of Central Committee members with ties to Hu Jintao that occurred after Hu Jintao was promoted at the 14th Party Congress. Also ties of Central Committee members to Jiang Zemin increased in and after the 14th Party Congress because Jiang Zemin forced Qiao Shi to retire and, at the same time, many of Shi’s followers left the Central Committee (ibid., 89, 99). Again, these events could cause changes in strategy both in the P.R.C. and the R.O.C. and hence changes in the coefficients which describe cross-strait dynamics.

Democratization For some time, scholars assumed that democracies are more willing and able to reciprocate cooperation than autocracies; audience costs in democracies were a much more effective constraint on dispute initiation in democracies than in autocracies (Guisinger and Smith, 2002; McGillivray and Smith, 2000). For this reason a change in regime type to democracy may amount to a change in a model regime which embodies relatively more reciprocity. Another well-established argument is that anocracies–regimes that are “intermediate” between autocracies and democracies–are comparatively more prone to civil war and other kinds of conflict (Hegre et al., 2001). More recent research has shown that different types of autocracies no more likely to initiate disputes than democracies, in particular, machine type autocracies in which leaders are nonpersonalist and audiences are

\footnote{Weeks (2008) coding scheme is based, in part, on the coding scheme in Geddes (2003). Weeks actually codes China as “interregna” for the years 1949-1951. But for the remainder of her data set, 1952-2001, she classifies the P.R.C. as “single.” In her newer work, Weeks (2012) classifies China under Mao as a personalist-civilian audience case, but China after Mao as an elite-constrained/civilian audience case. Svolik (2012) argues that because, among other things, Geddes categories are not mutually exclusive a new, five dimensional taxonomy is needed to study autocracy. His taxonomy, as we understand it, produces between 768 and 3840 different regimes. See Appendix for more details on the classification of our regime types by students of comparative authoritarianism.}

\footnote{Wu (2005, 59) links the Chinese power balance to P.R.C. policy toward the R.O.C.: “The weaker the [Chinese] leader's grip on power, the more intransigent he is when dealing with Taiwan. In China, the Party’s congresses are the functional equivalent to presidential elections in the US and Taiwan, in that there is jockeying among [Chinese] leaders in the run-up to a congress, and in this circumstance the paramount leader wants to seem popularly resolute to shore up his power.”}
composed of civilians. Autocracies with personalist leaders and military audiences—“juntas”, “bosses”, and “strongmen” are more likely to initiate disputes than democracies (Weeks, 2012). In these ways, changes in regime types may cause changes in conflict dynamics.

Since World War II, Taiwan’s polity has changed significantly. In the late 1980s and early 1990s Taiwan democratized. It now is considered a consolidated democracy. Theory argues that, in the period in which it democratized, the R.O.C. was most likely to cause war in the cross-straits. This is because in periods of democratization leaders are prone to use “nationalist prestige strategies” to try to maintain new political coalitions often composed, in part, of groups from the old autocratic regime, democratizing states are prone to conflict and war (Mansfield and Snyder, 1995). As noted above, in new democracies, the ability of mass publics to impose audience costs also is limited (Weeks 2008: 50). Now that the R.O.C. is a consolidated democracy, we should find that it is less likely to initiate conflict with the P.R.C. As for the latter, since Mao’s passing, China has been a “machine” autocracy, hence, on the basis of its regime type, we also would expect to be less likely to initiate conflict than autocracies of the alternative types.

As noted above, Pakistan’s polity has much to do with its history of conflict with India. The “structure, organization and ideology of the Pakistani state” is blamed for its behavior; “[the] features of the Pakistani polity prevented rational calculation of costs and benefits for warring with India” (Ganguly 2001: 7-8, 73). In contrast, the conventional wisdom seems to be that India’s democratic regime type makes it “less war prone . . . because of domestic crosscutting cleavages that make aggressive unilateral policy difficult to implement” (Tremblay and Schofield 2005: 236).15 Ostensibly then, India’s behavior ought to evidence more reciprocity than Pakistan’s behavior.

### 2.1.4 Stylized facts

**Phase shifts and the nonlinearity of conflict dynamics:** Much research suggests that intra and inter-state conflicts exhibit repeated phase shifts. A sample of the suggested number of phases and relevant citations is:

- 2 - Azar (1972), Senese and Vasquez (2003)
- 7 - Brahm (2003), Shields and Baldwin (2008)
- 8 - Vasquez et al. (1995)

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14 See the Appendix for more details on Taiwan’s regime type.

15 Ganguly (1997) attempts to test democratic peace theories in South Asia. His results are mixed. For instance, while he agrees that Pakistan’s military (autocratic) governments appear, at times, more war prone than India’s democratic government (p. 296), Ganguly points out that neither country was a developed democracy during the first war, India did not become especially belligerent during its bout of authoritarianism in the 1970s, it was India’s military maneuvers that precipitated the 1987 crisis, and throughout the conflict, larger geopolitical factors affected the course of the conflict (e.g., India’s defeat by China in 1962).
Theoretical explanations for phase shifts include repeated movement between multiple equilibria in games of incomplete information and invasion of dynamic version of such games by certain strategies (Diehl, 2006); path dependency (Huth and Allee, 2002a); multiple equilibria in strategies played by audiences and elites in two level games in (non)democracies (Rioux, 1998; Huth and Allee, 2002b) psychological triggers (Keashly and Fisher, 1996; Senese and Vasquez, 2008). As Schrodt and Gerner (2000) show, tracking these phase shifts can produce useful early warnings of conflict in the Levant and other regions of the world.

Operationally, phase shifts can be represented as switching models. The implication of the theoretical accounts listed above is that adversaries use different decision rules in each conflict phase. This means that the coefficients of the model equations that describe the dynamics in each phase are different. The conflict repeatedly switches between model regimes (equations) which have different coefficients representing the alternative strategies, dynamic equilibria, etc that constitute the different conflict phases. Unfortunately, researchers like those listed above provide few insights into the relative sizes of the transition probabilities between phases or into the structure of the equations that govern the dynamics in each phase.\footnote{Note that dummy variables and structural stability tests are not adequate to approximate or detect model regime switching of this kind. To begin, both the dummies and the tests condition on the data. The researcher often uses an ocular examination of the time series to construct the dummies or to select the possible breakpoints. For example, adding dummies for all elections (prime ministers) and for specific events like the Battle of Jenin (Brandt et al., 2008) may be unnecessary–these dummies may be proxies for what are actually conflict phase shifts. More important, contrary to the way dummy variables operate, the works cited above argue that these shifts are not be permanent, for example, that the constants in the equations for dynamics repeatedly change value suggesting recurring alterations in long-term equilibrium towards which the conflicts gravitate. Patterns of escalation and deescalation of conflict are illustrative.}

Put simply, to capture the key stylized fact of phase shifts in conflict dynamics we need to construct (nonlinear) multiequation time series models. Such models will not just allow for different dynamics in different conflict phases, they also will produce estimates of the probabilities of transitioning repeatedly between these conflict phases along with estimates of when these transitions occurred. To our knowledge no one who studies conflict phases has attempted to construct such a model.

\section*{2.2 Summary: Propositions}

Rationalist theories produce several falsifiable propositions.

\textbf{Proposition 1:} Short-term reciprocity produces long-term reciprocity in the behavior of belligerents. Where reciprocity has evolved, the transition probability from low to high conflict phases will be lower than in cases in which there is less evidence of reciprocity.

\textbf{Proposition 2:} Informational symmetries produce cooperation as mass publics (civilian audiences) reward cooperation and punish conflict. The transition probability from low to high conflict phases will be lower the higher the audience costs on each belligerent.

\textbf{Proposition 3:} Because they produce uncertainty for both leaders and selectorates and therefore changes in strategy, behavioral phase shifts should be evident during periods in which leadership successes occurs (whether by means of elections or elite negotiation). After one leader has succeeded another, there should be a shift in phase.
3 Our Test

3.1 Research Design

3.1.1 The Three Cases

To test our hypotheses and better characterize the stylized facts about conflict dynamics, we study the three cases discussed above: the conflicts between the Indians and Pakistanis, Chinese and Taiwanese, and Israelis and Palestinians. The first and second conflicts are widely recognized as rivalries of the enduring, strategic, and interstate types. The third is a conflict between a state and subnational entity (incipient state). All three conflicts embody asymmetries. Pakistan, Taiwan, and the Palestinians clearly have less military power than their adversaries, for example. Many observers, at times, have called these conflicts the most dangerous in the world and in their respective regions.

Most important, the cases differ on our independent variables. The degree of information asymmetry between elites and mass is much greater in China and Pakistan than the other countries. For the paired regime types, in each case one of the belligerents now is a well-established democracy. But each democracy have faced a different kind of adversary: an anocracy which has experienced several democratic reversals including some “strongmen regimes” (Weeks, 2012) and turned autocratic as recently as 1999 (Pakistan); a “machine” type autocracy with a nonpersonalist leader and civilian audience (China); and, a subnational, anocracy with periodic elections and a relatively attentive public (Palestine).

Roughly speaking we expect that Proposition 3 will be confirmed for India-Pakistan vs. the other cases because of the historically greater uncertainty produced by succession processes and more frequent change in regime type of Pakistan. Because of the lower prevalence of reciprocity in it, the short term probability of transitioning to a conflict phase in the India-Pakistan case should be greater in magnitude than in the other two cases as well.

3.1.2 Measures and Data

The Event Data Project at Pennsylvania State University is the main source for our data. The event data we employ here were coded from news feeds using the CAMEO even coding ontology (Gerner et al., 2009). CAMEO codes dyadic events between actors A and B into categories of verbal and material conflict/cooperation. For the analysis here, we have selected actors that represent the main interactions in each conflict. So for the Levant we focus on Israel and Palestine; China and Taiwan for the Cross-Straits, and India and Pakistan for the Subcontinent. The data are aggregated into monthly time series for different time periods.

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17 On the rivalry classification of the Indian-Pakistani and China-Taiwan cases see Colaresi et al. (2007, Table 2.1). Both rivalries are classified as ongoing and fulfilling most of the criteria for all types of rivalry.
18 In 2000, President Clinton called the India-Pakistani conflict the most dangerous on earth (Ganguly, 2001, 1). The cross-strait conflict has been called the most dangerous flashpoint in Asia by several commentators (Hickey, 2006, 463, 465).
19 See the appendix for more information on the paired regime types, including figures for their polity scores between 1947 and 2010.
20 This is clearly a constraint. But if we do not find phases in conflict among the main actors, looking at more dyads is not going to make this inference easier.
The Levant dataset includes dyadic Israeli (I) and Palestinian (P) net directed verbal (V) and material variables (M). This generates four time series: I2PV, P2IV, I2PM, and P2IM.\textsuperscript{21} Figure 1a plots these monthly series from 1979(4)–2011(11). The Cross-Straits data have similar directed net dyadic measures for Chinese (C) and Taiwanese (T) actions, producing variables C2TM, T2CM, C2TV, and T2CV, over 1998(1)–2010(4) in Figure 1b. The final, Indian Subcontinent dataset has similarly constructed data for Indian (I) and Pakistani (P) interactions producing variables I2PV, P2IV, I2PM, and P2IM over the months 1998(1)–2011(2), displayed in Figure 1c.

3.1.3 Method: A model for multivariate time series with regime changes

For reasons explained elsewhere (Brandt et al., 2011; Brandt and Freeman, 2009, 2006) the Markov switching Bayesian vector autoregressive model (MSBVAR) is best suited to analyze conflict dynamics. This model allows for repeated phase shifts in what is a multiequation model of endogenous behavior between each pair of belligerents. Analysis of the fitted model produces insights, among other things, into the transition probabilities between phases, the timing of phase shifts historically, and the evolution of reciprocal (vs. inverse) behavior.

Building our models is a process of dynamics specification. This is accomplished in three steps. First, we must determine the number of phases or regimes that best describe the data and the number of lags necessary to account for the dynamics. Second, we must determine how the regimes differ: do the best fitting time series models have different intercepts, variances, or dynamics that characterize the differences across the regimes? Finally, we need to estimate the models using the structural identification information so that we can behaviorally interpret and explain what occurs in each of the regimes.

To determine the number of conflict phases in our multivariate time series of conflict / cooperation data, we employ a regime-switching model for multivariate time series. Let $y_t$ be the observed $m$–dimensional time series at time $t$ for $t = 1, \ldots, T$. For each time point there is also a discrete state variable $s_t = k$ for $k \in \{1, 2, \ldots, h\}$. Here $h$ is the maximum number of phases or regimes needed to account for the potential phase dynamics. At first we assume this is known and then discuss strategies for testing or evaluating the choice of $h$.

The goal of the model is to fit and determine the dynamic process for both $(y_t, s_t)$ for $t = 1, \ldots, T$. To jointly construct and estimate the probability $\Pr(y_t, s_t)$ and partition out the information about the conditional probabilities $\Pr(y_t|s_t)$ and $\Pr(s_t|y_t)$. The former probability (and its model) describe the behavior or dynamics of the dyadic interactions given the regimes or phases. The latter, regime probability conditional on the data, are generated by a state-space filter that estimates the regime probabilities, given the data.

The latent regime probabilities are assumed to follow a first order Markov process. Let $Q$ be the $h \times h$ Markov transition matrix whose rows sum to 1. The elements $q_{ij}$ give the

\textsuperscript{21} Across this time period, we combine the together the possible Palestinian actors such as the PLO, Hamas, Fatah etc. The list of actors we use, based on the CAMEO dictionaries, are NGMPAL, NGOPAL, PAL, PALCVC, PALEG, PALLAB, PALMED, PALMOS, PALMOSREB, PALPLO, PALREB, PALREBANO, PALREBPLF, PALREB, PSE, PSECHE, PSECOP, PSELI, PSEGOV, PSEGOVMED, PSEGZSREB, PSELEG, PSEMED, PSEMIL, PSEMILJUD, PSEOS, PSEP, PSEOPP, PSERAD, PSEREB, PSEREBAAM, PSEREBDFL, PSES, PSEWN, PSEWBWNREF, PSEGZS, PSEGZSREB, PSEGOVH, PSESEGZS, PSEGZSMD, PSEGOVFTA, PALPLO, and PSERFBAEI.
Figure 1: Conflict data for the Levant, Cross-Straits, and the Indian Subcontinent. See text for definition of the variables.
probabilities of transitioning from state $s_{t-1} = j$ to $s_t = i$, or $\Pr(s_t = i|s_{t-1} = j)$. If we assume that there are regime-specific dynamic parameters $\theta_k$ for each of the $h$ regimes and that $\Theta = (\theta_1, \theta_2, \ldots, \theta_h)$ is the set of parameters for each regime, then we can construct the joint probability model as

$$\Pr(y_t|\Theta, Q) = \prod_{t=1}^{T} \left( \sum_{s_{t-1}=1}^{h} \Pr(y_t|Y_{t-1}, \Theta, s_t) \times \Pr(s_t|Y_{t-1}, \Theta, Q) \right), \quad (1)$$

where $Y_{t-1}$ is the history of $y_t$ for a given transition matrix $Q$. Note that if $y_t$ is multivariate or represented by a time series model of even minor complexity, the size of the parameter space for any give $\theta_k$ is going to be large.\footnote{For the MSBVAR model we propose here, for each regime, $\theta_k$ for the $k^{th}$ regime will have $m^2p + m + 0.5m(m+1)$ unique parameters for a reduced form VAR model with $m$ equations and $p$ lags.}

This is a general formulation of a Markov-switching time series model (e.g., Hamilton, 1989, 1990; Kim and Nelson, 1999; Sims et al., 2008). Standard filtering and smoothing algorithms in the literature are used to estimate the regime probabilities $\Pr(s_t|y_t)$ (Kim and Nelson, 1999). The remaining choice to complete the model in Equation (1) is the choice of the model for $\Pr(y_t|s_t)$. Since $y_t$ are our dyadic time series, we employ a regime-specific vector autoregression. Assuming the states, $s_t$ are known the model for the observed data is

$$y_t = c(s_t) + \sum_{t=1}^{p} y_{t-\ell} B_t(s_t) + c(s_t), \quad (2)$$

$$\epsilon_t(s_t) \sim N(0, \Sigma(s_t)) \quad t = 1, 2, \ldots, T, \quad (3)$$

where $c(s_t)$, $B_t(s_t)$, $\epsilon(s_t)$, $\Sigma(s_t)$ are the regime specific constants, autoregressive coefficient matrices, residuals, and error covariance for a VAR($p$) models for regimes $s_t = i$, $i = 1, 2, \ldots, h$. Here we assume $p$, the VAR lag length is known (more on this below). The parameter in Equation 3 for a given regime $k$ make up the parameter space $\theta_k$ for regime $k$.

This type of model is capable of capturing the highly complex phase dynamics (4 or more regimes) of multivariate time series data (e.g., in monetary policy regimes with structural restrictions, see Sims et al., 2008). This is exactly what the literature on international and regional conflict have posited could exist (without explicit testing). Here is a model that can be used to identify and test the number of regimes and their dynamics.

It is however possible that the inference and interpretation of such a model outstrips our ability to identify it in the data. The theoretical models that posit multiple regimes may be artifacts: they may be conditioned too closely on specific cases and ignores simpler structures that represent the observed data frequencies and dynamics with simpler models (Tetlock, 2005; Taleb, 2010). The result is that the literature’s narratives about conflict may be much more elaborate than the actual data – either because of measurement or statistical simplifications (Hastie, 2012).

### 3.1.4 Priors and Bayesian Estimation

Given the large, complex parameter space for the Markov-switching VAR (MSVAR) model outlined for our evaluation of the number and dynamics of conflict regimes, we employ
Bayesian methods. A particularly useful prior for the model has the form

\[ Pr(\Theta, Q, S_T) = Pr(\Theta) \cdot Pr(Q) \cdot Pr(s_0|\Theta, Q) \cdot \prod_{t=1}^{T} Pr(s_t|\Theta, Q, S_{t-1}) \]  

(4)

where \( s_0 \) is the initial state with prior \( 1/h \), \( s_t \) are the regime indices, and \( S_{t-1} \) is the previous state path. Here the joint prior over \((\Theta, S_T, Q)\) has been partitioned into a conditional prior where the regime-specific VAR parameters have a Sims-Zha prior (Brandt and Freeman, 2006; Sims et al., 2008).²³

Under this prior, the resulting conditional posteriors are (Sims et al., 2008):

\[ Pr(S_T|Y_T, \Theta, Q) \propto Pr(s_t|S_T), \quad \forall t \]  

(5)

\[ Pr(Q|Y_T, \Theta, S_T) \propto \prod_{i=1}^{h} p_{i,j}^{n_{i,j} + \alpha_{i,j}} \]  

(6)

\[ Pr(\Theta|Y_T, S_T, Q) \propto N(\hat{\Theta}, \hat{\Sigma}) \]  

(7)

We implement a Gibbs with Metropolis Markov chain Monte Carlo sampler with random permutation of the regime labels for these conditional densities (Frühwirth-Schnatter, 2001, 2006; Sims et al., 2008). The sampling steps for \( S_T \) and \( \Theta \) are well documented Gibbs sampling steps (inter alia, Sims et al., 2008; Krolzig, 1997), while the sampling for \( Q \) and the random permutation steps are discussed in Frühwirth-Schnatter (2001, 2006). For the models with identified regimes, we have used a k-means clustering algorithm of the posterior draws to determine which parameters identify the switching.

### 3.1.5 Determining the number of regimes, order of the dynamics, and the regime labeling

The assumption in the model outlined in Equations (1) and (3) is that the number of regime, \( h \), and the number of VAR lags, \( p \), are known. These choices however are the central inferential questions of this paper since their choices determine the number of conflict phases and the possible reciprocity (and later, triangularity) relationships in the data (Brandt et al., 2008).

To choose the values of \( p \) and \( h \), we need a general model fit measure. For a Markov-switching Bayesian VAR (MSBVAR) a natural candidate is the log marginal data density. The log marginal data density is the normalizing constant of the posterior distribution and

²³Using the parameterization for the Sims-Zha prior from Brandt and Freeman (2006), we set \( \lambda_0 = 0.8, \lambda_1 = 0.15, \lambda_3 = 1, \lambda_4 = 0.2, \lambda_5 = 0, \mu_5 = 0, \) and \( \mu_6 = 0 \). This is a weakly informed prior that is symmetric across the regimes. The prior on \( s_0 \) is uniform. The prior on \( Q_h \) is Dirichlet, or \( D_h \):

\[ D_2 = \begin{pmatrix} 10 & 2 \\ 2 & 5 \end{pmatrix}, \quad D_3 = \begin{pmatrix} 10 & 2 & 2 \\ 2 & 5 & 2 \\ 2 & 2 & 2 \end{pmatrix}, \quad D_4 = \begin{pmatrix} 10 & 2 & 2 & 2 \\ 2 & 8 & 2 & 2 \\ 2 & 2 & 6 & 2 \\ 2 & 2 & 2 & 4 \end{pmatrix}, \]

for \( h = 2, 3, 4 \).
gives the log posterior probability that the parameterization of the model generated the data. It can be computed from the randomly permuted MCMC output using the methods described in Frühwirth-Schnatter (2006). Specifically, we implement a posterior bridge sampler to integrate the log marginal likelihood estimate over the MCMC output, with a set of auxiliary sampling steps. Among the multiple methods that can be employed for this computation (see, Gamerman and Lopes, 2006; Meng and Wong, 1996) the bridge sampler has the smallest standard error for Markov-switching models (Frühwirth-Schnatter, 2006).

To make the choice of \( p \) and \( h \), for each of our three datasets, we fit a series of models for values of \( p = \{1, 2, \ldots, 5\} \) and \( h = \{2, 3\} \). For each model we estimate the log marginal data density with a posterior bridge sampler. Figure 2 plots the log marginal data density values for choices of \( p \) and \( h \) across the three datasets.

For the Levant dataset, the best choices are \( p = 1 \) and \( h = 2 \), or a one VAR lag with two regimes MSBVAR specification. For the Cross Straits and and Indian Subcontinent datasets, the best fitting model has \( p = 1 \) and \( h = 3 \). (The same results are also presented in Tables 4–6.) One practical issue with these choices is that the log marginal likelihood tends to choose models that potentially overfit the data or have regimes that are mixtures of each other. So in the sequel we will see that 2 regime models are more than adequate since the three regime models generate 2 regimes that are mixtures of a single regime or have too few observations too be properly identified (i.e., there are too few datapoints classified into the
3rd regime).

Note, this is in contrast to some earlier analyses of similar data that find longer lag length selections or value of $p$ (Brandt et al., 2008; Brandt and Freeman, 2006; Goldstein et al., 2001). The reason the MSBVAR model has a lower order of lags $p$ than previously seen in this kind of event data is a result of the Markov-switching aspect of the model. Krolzig (1997) shows that VARMA($p^*$, $q^*$) have MSBVAR($p, h$) representation with $p \leq p^*$ since the remaining dynamics are captured by the Markov-switching process.\footnote{Another potential source of the difference here is the level of aggregation used across different studies. On this point see Freeman (1989); Shellman (2004); Zeitzoff (2011).}

An issue with the Gibbs sampler that we implement is that it is invariant to the labeling of the regimes, meaning that the posterior distribution has $h!$ possible modes, which are explored equally with the random permutation sampler. This is not an issue for inferences about the number of regimes or the lag length, but it means that the regime labeling information is lost. To recover this information we employ a k-means clustering of the posterior parameters to identify whether the regimes have different intercepts, autoregressive terms, or variances across the regimes. We conduct this analysis separately for each of the three datasets and the optimal choice of $p$ and $h$, based on the results in Figure 2.

Of interest then, is which parameters differ the most across the regimes for each dataset. For the Levant dataset the regimes differ most in their variances and intercepts. Figure 3 shows a paired scatterplot of the posterior k-means clustered variance output from the MSBVAR model for the Levant data. The plot gives the comparison of the posterior MSBVAR error variances across the four equations. Here, there is one very low variance regime (in red) and a high variance regime (in black). So the differences in the variances across the regimes can be used to identify and explain what occurs in each regime.\footnote{The regimes also differ in their intercepts or dynamic equilibria. But the separating hyperplane in the variances is much clearer and leads to a better estimate of the identified posterior regimes than using the regime-specific intercepts to identify the differences across the regimes.}

To get identified regime probabilities and posterior samples we impose the condition that the variances in the $I2PM$ equation need to be ordered across the regimes. For the Cross-Straits data, the clearest differences across the regimes are in terms of the intercepts. The scatterplots the the MSBVAR equation intercepts in Figure 4 show a clear hyperplane in the intercepts of of the $C2TV$ and $T2CV$ equations — or that the verbal cooperation / conflict measures separate this “cold” conflict. This is good confirmation for our earlier suggestions that the differences in possible conflict regimes are driven by different interactions across different conflicts.

Of note in Figure 4 is the combination of clustered intercepts for the $C2TM$ and $T2CM$ equations. These are quite scattered and give the reason why the log marginal data density fit criteria selected the three regime model for these data. A three regime model better captures these changes in the intercepts on this criteria, but there are too few observations to accurately measure the differences across these regimes. Part of the reason why is seen in the upper left corner of the scatterplots: there is a very tight clustering of the values over a range ($-0.6, 0.2$), which is quite narrow and hard to differentiate regimes for variables with the variation seen in Figure 1b. With a longer dataset, it might be possible to identify a third regime in the Cross-Straits data.

Finally, Figure 5 presents the posterior clustered intercepts of the randomly permuted
Figure 3: Scatterplot of the posterior clustered variances for the Levant 2 regime model. Results from k-means clustering of the MSBVAR equation variances from the Levant model. Each plot is the comparison of the posterior residual variances of MSBVAR equation $i$ to equation $j$ ($i \neq j$).
Figure 4: Scatterplot of the posterior clustered intercepts for the Cross-Straits 2 regime model. Results from k-means clustering of the MSBVAR equation intercepts from the Cross-Straits model. Each plot is the comparison of the posterior intercepts of MSBVAR equation $i$ to equation $j$ ($i \neq j$).
Figure 5: Scatterplot of the posterior clustered intercepts for the Indian Subcontinent 2 regime model. Results from k-means clustering of the MSBVAR equation intercepts from the Subcontinent model. Each plot is the comparison of the posterior intercepts of MSBVAR equation $i$ to equation $j$ ($i \neq j$).

posterior for the two regime model for the Indian Subcontinent data. Here we see again a) why the two regime model fits well for the I2PV and P2IV equation intercepts, and b) the mixed evidence for a third regime in the net material conflict data series.

There is a possible third regime in the material conflict series for the Indian Subcontinent conflict. While a different prior might be able to be employed to tease out the differences across the regimes, at present the three regime variant of the model does not have enough observations in it to be able to sort out the differences in a possible second or third regime. Alternatively, the limitations of only employing 159 monthly observations might be limiting our abilities to make more refined regime inferences.

Using these differences across the MSBVAR parameter spaces for the chosen values of $p$ and $h$ for each conflict, we next fit models that respect the regime identification restrictions outlined in this section. The next section reports the results for these models.
3.2 Results

Identified regime MSBVAR models are the main inferential result reported here. These are the main inputs to for our comparative analysis of regional conflicts and their dynamics in the Levant, Cross-Straits, and Indian Subcontinent cases. For each of the regime identifications discussed in the last section, we re-estimated the MSBVAR model using a burnin of 20000 iterations and a final posterior sample of 100000 draws. Figures 6a–6c show the estimates regime probabilities for the two regime models for each conflict. These give the probabilities of being in either regime 1 (black) or regime 2 (red). For the longer Levant dataset, it is much easier to recover and identify the regimes because of the greater information in the dataset. Figure 6a indicates that there is a fair amount of switching over the 392 monthly observations.

There is much less switching in the Cross-straits and Indian subcontinent models. For the Cross-straits data, the regime only changes briefly in 2005. In the Indian Subcontinent case the second regime is visited for a brief period in mid to late 1999.

For the identified regime models we use a more diffuse prior for the switching process in $Q$. This allows the data to do the majority of the work in constructing the posterior inferences about the regimes. It also reflect that fact that a priori we are agnostic about the length or structure of the possible Markov-switching process of the regimes.\footnote{Specifically, we use a weakly informed prior on the Dirichlet distribution of the transition matrices.} The posterior transition matrices for each model are

$$Q_{	ext{Levant}} = \begin{pmatrix} 0.95 & 0.05 \\ 0.39 & 0.61 \end{pmatrix}, \quad (8)$$

$$Q_{	ext{Cross-Straits}} = \begin{pmatrix} 0.49 & 0.51 \\ 0.06 & 0.94 \end{pmatrix}, \quad (9)$$

$$Q_{	ext{Subcontinent}} = \begin{pmatrix} 0.96 & 0.04 \\ 0.55 & 0.45 \end{pmatrix}. \quad (10)$$

Since the dominant probability is on the main diagonal for the Levant data, this is why we see more persistence in the regimes. For the Cross-straits and Subcontinent datasets, the probability of staying in one of the regimes is quite low (since some of the off diagonal entries are larger than those on the main left-right diagonal of $Q$). If a more informed prior were chosen for the switching — one that put more prior belief on the idea that there are persistent regimes — then these posterior matrices and the regime probability plots in Figures 6a–6c would change. Future sensitivity analysis will evaluate the effect of this prior.

The Markov transition matrices have a long run distribution over the states. This is computed for an given transition matrix $Q$ as follows: Define $Q_{1:h-1,1:h-1}$ as the first $h - 1$ rows and columns of $Q$. Now construct the matrix

$$\hat{Q} = \left( \left( I_{h-1} - Q'_{1:h-1,1:h-1} \right) | Q'_{1:h-1,1:h} \right) \times \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}^{-1}$$

$26$Specifically, we use a weakly informed prior on the Dirichlet distribution of the transition matrices.
Figure 6: Regime probabilities for each conflict. Regime probabilities are indicated by red and black lines.
Table 2: Long run regime probabilities for each conflict. 95% credible intervals in parentheses

<table>
<thead>
<tr>
<th>Conflict</th>
<th>Regime 1</th>
<th>Regime 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levant</td>
<td>0.97</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.94, 0.99)</td>
<td>(0.001, 0.06)</td>
</tr>
<tr>
<td>Cross-Straits</td>
<td>0.95</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(0.04, 0.99)</td>
<td>(0.001, 0.96)</td>
</tr>
<tr>
<td>Indian Subcontinent</td>
<td>0.97</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.94, 0.99)</td>
<td>(0.001, 0.06)</td>
</tr>
</tbody>
</table>

where $I_{h-1}$ is an identity matrix of dimension $h - 1$, $1_h$ is a vector of ones, and the last vector has $h - 1$ zeros and then a 1. The solution to this, $\hat{Q}$ will be an $h \times 1$ vector the long run probabilities of being in each regime.

Using the posterior sample, we can estimate the long run probabilities for each of the three two regime models. Table 2 give the long run probability of being in each regime. For the Levant and Indian Subcontinent cases these probabilities are sharply estimated. For the Cross-Straits case the 95% credible intervals are quite wide. This is evidence either a) that the regimes are misidentified in the posterior sample, b) that there is little to any real switching in the data, or c) that the diffuse prior is incorrect and that a more informed prior should be used. The mis-identification of the differences in the parameters across the regimes would be consistent with the scatterplot of the intercepts, Figure 4.

A key conclusion here is that the two well identified models, the Levant and the Indian Subcontinent have similar long run regime probabilities. In terms of generalizations, this is critical, since it means that the low versus high conflict regimes have similar likelihoods across the two conflicts. This is a critical generalization since it speaks to how we describe generalizations across conflicts, which is a common occupational hazard.

To see further how the regimes differ one can look at the densities of the posterior for each regime in each conflict. Figure 7 is the first of these density plots for the identified Levant MSBVAR model. Since these are two regime, one lag models, we construct a matrix of plots that corresponds to the $m^2p + m = 4^2(1) + 4 = 20$ coefficients for each regime. The plots give the $4 \times 4$ matrix of AR(1) coefficients for each regime’s VAR. Separate colors are used to identify the density of the parameters in each regime. The last row of the plot gives the intercepts for each equation. So each column of plots corresponds to the coefficients for a given equation in the VAR for that regime.

Recall from the earlier discussion that the main difference in the regimes for the Levant data are the VAR error variances (see Figure 3). The regimes are required to have different variances for the I2PM equation. The variance in the first regime is the smaller of the two. The resulting MSBVAR regression estimates are in Figure 7. The regime parameters plotted in black correspond to the low volatility regime, while those in red are the high volatility regime regression parameters. Looking down the main left-right diagonal of the Levant autoregressive coefficients, we see that in general the high volatility (red) regime has more persistent dynamics since the autoregressive effects are closer to 1. Note also that the differences in the intercepts across the two regimes are not that large. So the defining characteristic in the dynamics of the Israeli-Palestinian conflict are not about the levels of
Figure 7: Levant MSBVAR posterior estimates. Coefficients for the MSBVAR with 2 regimes and 1 lag. Columns of plots correspond to the equations, rows to the lagged variables. The intercepts are in the last row of plots.
conflict over the regime. Rather the conflict varies much more in terms of its volatility across the regimes.

The same plots for the Cross-Straits dats MSBVAR model are presented in Figure 9. The regimes in model were identified by the ordering of the intercept of the C2TV equation. The mean of the intercept for this equation is 3.65 in the first (black) regime and 5.48 in the second regime (red). While the densities for regimes are different across the key dynamic parameters, there is little difference that separate the regimes since the second regime is so rare. Behaviorally, the differences across the intercepts in this model indicate that there are differences in the verbal conflict / cooperation measures that differentiate the regimes. The same is not true of the material conflict equation intercepts which overlap across the two regimes.

In the Cross-Straits MSBVAR posterior parameter densities in Figure 9 there is considerable multi-modality. Looking at the results this way one can see why there was evidence for a three regime model, since many of the densities have three or more modes. What needs to be determined is the length of the possible regimes so that a suitable prior density can be chosen for Q so that the regimes can be identified. Looking back at Figure 1b, there is not clear basis for forming a prior over the length and probability of the regimes. This will clearly be an area for future research.

Figure 9 presents the posterior parameter estimates for the MSBVAR for the final conflict Indian Subcontinent analysis. Recall, this model’s regimes were identified with a restriction on intercept of the I2PM equation. Here we see separate modes with values of -1.88 in the first regime and -1.38 in the second regime. Again, we see the same issues as in the Cross-Straits analysis: there is multimodality that indicates possible other regimes, but we have limited information with which to identify the possible dynamic parameter differences across the regimes.

Of significance is that we find little evidence of higher numbers of regimes in the absence of identification information that would tease out the dynamic relationships within and across regimes or phases. The key of the comparison conducted here is that there is going to be futility in a “single” model or theory of conflict dynamics.

A final set of inferences can be found by tracing out the impulse response function (IRF) dynamics for each regime and averaged over the regime probabilities. The latter we refer to as equilibrium impulse responses and they weight the impulse responses for each regimes by the long run probabilities in Table 2. Figures 10–12 give the regime specific and equilibrium impulse responses based on a simple Cholesky decomposition of the error covariances for conflict. The reported 68% credible intervals apply the Bayesian shape error band method explicated in Brandt and Freeman (2006). Recall that since we are fitting reduced form

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We generate these IRFs using a modified version of the approach detailed in Brandt and Freeman (2006). For each posterior draw for each regime we construct the Cholesky decomposition of the error covariance to represent the reduced form pattern of shocks (conditional on the ordering of the variables in the VAR equations). Next, we use the autoregressive coefficient(s) for each regime and draw to compute the appropriate vector moving average of the responses given the orthogonalization of the shocks. Then we compute the long run regime probabilities for that draw. We use these long run regime probabilities to average other the regime-specific impulse responses to compute the equilibrium impulse responses. Finally, we repeat this process 100,000 times. We summarize the 100,000 posterior impulse responses using the Bayesian shape error band method of Sims and Zha (1999).
Figure 8: Cross-Straits MSBVAR posterior estimates. Coefficients for the MSBVAR with 2 regimes and 1 lag. Columns of plots correspond to the equations, rows to the lagged variables. The intercepts are in the last row of plots.
Figure 9: Indian Subcontinent MSBVAR posterior estimates. Coefficients for the MSBVAR with 2 regimes and 1 lag. Columns of plots correspond to the equations, rows to the lagged variables. The intercepts are in the last row of plots.
MSBVAR models, the interpretation of the Cholesky orthogonalization of the errors depends on the ordering of the equations (among \( n! \)) possible orderings. So in our interpretation we focus here on general patterns of dynamic responses, leaving it for future work to explore different structural representations of the dynamics (cf., Brandt and Freeman, 2009).

Figure 10 are the impulse responses for the Levant case where we have ordered the equations as seen in Figure 1a with the verbal conflict / cooperation equations ahead of the material conflict / cooperation equations. The larger variance in the second regime (documented above) is seen in the size of the shocks to the equations in Figure 10b. This reflect the identification of the regimes made earlier, since the shocks in regime 2, in Figure 10b are nearly twice as large as those seen in Figure 10a. There are also differences in the reduced form dynamics and their reflects in the IRFs across the two regimes. Responses are larger in regime 1 compared to regime 2 for the Levant. Further, the regime 2 impulse responses have a slower return to zero, meaning that shocks are larger and more persistent in this second regime.

In the long term or equilibrium Levant IRF (Figure 10c) we see the dominance of the regime 1 results, since these are the more likely outcome based on Table 2. Long term there appears to be actual reciprocity in the responses to positive shocks in the I2P and P2I equations. Note that this depends on the particular ordering of the equations in the Cholesky decomposition of the error covariance and that this results needs to be checked for other orderings of the equations.

Figure 11 provides a similar set of impulse responses for the Cross-Straits case. Here we see the effects of the potentially uncertain identification of the regimes. Despite the apparent stationarity of the Straits data in Figure 1b, the impulse responses (identified across the regimes with intercept shifts) look non-stationary. Over a 12 month horizon, the responses to the verbal shocks (columns C2TV and T2CV) appear to diverge from zero rather than equilibrate shocks back toward zero. Average over the regime probabilities, the equilibrium IRFs for the Cross Straits appear more stable. There is clearly more room for detailed research about the dynamics and possible regime differences for this case. Given the data, other possible regime identification and inference strategies need to be pursued to make sense of the dynamics in this conflict and what they mean.

Finally, Figure 12 gives the impulse responses for the MSBVAR models for the Indian Subcontinent case. In this final case, the dynamics of the second regime show a larger verbal reciprocity response over 12 months than is seen in the first regime. Positive shocks to I2PM lead to negative verbal responses by both parties in the second regime, but no responses in the first regime. There is evidence of positive reciprocity responses in P2IM when there there are positive shocks in I2PM in the first regime, with an even strong response in the second regime. Positive Shocks to the verbal equations in the second regime lead to negative material responses (lower right hand corner of Figure 12b. In sum, we again see different dynamic patterns for the given ordering of the Cholesky decomposition in this model, compared to the other conflicts and even among the regimes in the same conflict. The equilibrium responses in the Subcontinent conflict are dominated by the first regime (see Table 2), but reflect the mixture over the possible shock-response combinates seen in regime 2, or Figure 12c.
Figure 11: Regime-specific and equilibrium, regime-averaged impulse responses for the Cross Straits. Based on a Cholesky decomposition of the regime-specific error covariances. Error bands are 68% credible intervals computed using the Bayesian shape method of Sims and Zha (1998). See text for definition of the variables.
Figure 12: Regime-specific and equilibrium, regime-averaged impulse responses for the Indian Subcontinent. Based on a Cholesky decomposition of the regime-specific error covariances. Error bands are 68% credible intervals computed using the Bayesian shape method of Sims and Zha (1998). See text for definition of the variables.
4 Discussion

The results inform rationalist theory as well as empirical research on conflict dynamics.

Proposition 1: There is evidence of the evolution of cooperation but also of substantial differences in ways this cooperation unfolds in the different cases. The fitted models illuminate connections between short run patterns of reciprocity, the propensity to shift between conflict phases, and long-run equilibration. They suggest that when, in the short-term multiple regimes evidence reciprocity, this reciprocity is manifest long term as well. But the long-term pattern of behavior need not always connote cooperation. Patterns of inverse responses, as in the Levant, appear in the long-term equilibrium dynamics. An example is the inverse material response of the Palestinians to positive shocks in verbal cooperation from the Israelis; similarly, the unresponsiveness of the Israelis to positive shocks of verbal and material cooperation in the short term is reflected as well in the equilibrium IRFs for the Levant. Interestingly, this result for the Levant is the opposite of what Zeitzoff (2011) found for the Gaza conflict. On the Indian subcontinent, while there are some reciprocal responses by the Pakistanis in the short and long terms to cooperative initiatives by India toward Pakistan, the opposite is not true in either the short term or the long term. This appears to be consistent with the argument that Pakistan has difficulty signaling its intentions and objectives (Tremblay and Schofield, 2005).

In addition, the results suggest that the data generating processes for Levant and Indian subcontinent are different kinds of mixture distributions. They are a mix of model regimes with different variances and different intercepts, respectively. The former connotes a process that seeks an (a vector of) equilibrium (levels) but switches between periods with different variances as if, at these times, the agents had difficulty deciding their decision rules (see Freeman et al., 2000). The latter mixture distribution suggests a stochastically stationary process but one which switches between processes with a different long term expected values. In this sense, the evolutionary, out-of-equilibrium behaviors (Diehl 2006) in the Levant and Indian subcontinent are distinct.  

Proposition 3 Recall that the rationalist argument holds succession processes and regime change are major sources of uncertainty. Hence we should expect phase shifts at or near times at which elections, democratic reversals, and related events occur. With one exception, there is little support for this argument in our results (Figure 6). The exception is the regime change that occurred in Pakistan in the late 1990s (see Appendix). This shift does suggest that a change in regime type may alter the decision rules of agents and hence the coefficients of the equations that describe their behaviors. A longer time series for the Indian subcontinent might be more revealing. But, interestingly, the Levant model is based on a much longer time series, and it indicates phase shifts at numerous time points that do not correspond to Israeli (or to the handful of Palestinian) elections. So, at this point, Proposition 3 is not supported.

Stylized facts about conflict dynamics: If there is a general result here it is that conflict dynamics differ greatly across our three cases; there is no one singular pattern of behavior.

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28 For a discussion of stochastic stationarity for nonlinear time series models in political science see Freeman, 2012a. Although our results here for the cross straits model for both verbal and material behavior seems to imply nonstationary, Freeman (2012b) finds that a TAR model fits the cross straits case for material behavior only.
Our cases include two major rivalries. Hence their “action-reaction” sequences differ from nonrivalries (Colaresi et al., 2007). But these rivalry cases also display different behaviors. There are clear short and long run differences in patterns of verbal and material responses in the Cross Straits and Indian Subcontinent. These patterns differ from those of the Levant as well. The size of these responses and their speeds of reequilibration differ greatly. There also are major differences in regime dynamics within particular cases. In the Levant, for instance, the verbal reciprocity patterns differ across the two regimes; they are much stronger in the high volatility regime. To explain these differences, we much delve deeper into the psychological and other literatures cited above (e.g., Senese and Vasquez, 2008).

For phase shifts inferences, the results—which at this point are based on what are essentially uninformative prior information—show that these three major conflicts are characterized by a small number of regimes. The proponents of 4-8 regime shifts appears to have fallen victim to the pitfalls of ad hoc pattern hunting (Taleb, 2010). From a research design standpoint, of course, the small number of regimes is encouraging. If this result holds up, computational burdens will be less than if larger numbers of regimes were found.

5 In Lieu of a Conclusion

As the reader no doubt noticed, we have not evaluated two-level rationalist theory, or Proposition 2. We have public opinion data from our previous investigation (Brandt et al., 2008) and several new series for Taiwan that can be used for this purpose. Future versions of the paper will report these results.

In many ways, our work demonstrates the problem of “Empirics Ahead of Theory.” Simply put, the connection dynamic rationalist theory and the properties of reduced form, multiequation time series models (VAR, BVAR) was much easier to make than the connection between this body of theory and MS-(B)VAR models. Among other things, understanding how the behavioral dynamics captured by the regime equations are related to the phase dynamics embodied in the changes in the transition probability matrix over time, is not yet clear. We have much to learn about how best to jointly set the priors for Q and Θ. Our IRFs are based on reduced form MS-BVAR representations of the data. We have assumed a particular ordering of the variables/equations in the Cholesky orthogonalization of the error covariances. We clearly need to explore other orderings: putting the verbal equations after the material ones and perhaps changing the order of the variables in the models. Regardless of these specifications, many of the differences in dynamics of the three conflicts are sure to remain. Only their substantive interpretations will differ.

Finally, more work obviously is needed on the Cross Straits case. Additional identifying information is need to make sound regime inferences. It is clear from the discussion above that, at present, we only have the vague idea how to do this. For instance, in comparison macroeconomics, it is not as simple as with GDP growth data for which one can order the regimes by periods of expansion or contraction (cf., Hamilton, 1989). Alternative priors for the Cross Straits model are called for in future analyses. And, several key variables like

29Note that this result differs from the negative reciprocity (inverse behavior) reported in Brandt et al. (2008) mainly because there the authors used WEIS coded data scaled with Goldstein scores and here we analyze separate net cooperation and net conflict measures coded using the CAMEO ontology.
public opinion and trade probably need to be added to it (Lin et al., in progress).
References


Shellman, S., A. Reeves, and B. Stewart (2007). *Fair & Balanced or Fit to Print? The Effects of Media Sources on Statistical Inferences*. University of Georgia.


6 Appendix

6.1 Regime Type Pairs

6.1.1 Pakistan and India


None of these authors classifies India as autocratic in any period. The Polity charts for Pakistan and India are as follows:

Figure 13: Polity Scores for Pakistan, 1945-2010. Source: Polity Website; www.systemicpeace.org

6.1.2 China and Taiwan


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30Svolik’s classification ends in 2008
Figure 14: Polity Scores for India, 1945-2010. Source: Polity Website; www.systemicpeace.org

(2012) classifies Taiwan as “strongman regime,” “machine regime,” and democracy in the periods 1949-1974, 1975-1991, and 1992-1999, respectively. The same author classifies China as “other authoritarian” between 1946-1948, “boss regime” between 1949 and 1976, and a “machine regime” between 1977-1999. Svolik (2012, Chapter 2) classifies China as having experienced an “authoritarian spell” during his entire data set, 1946-2008.\footnote{Svolik argues that autocracies are best distinguished in terms of five independent dimensions: military rule, restrictions on parties, legislative selection, executive selection and constitutional foundation. Each dimension has a number of categories. This implies that there could be as many as 3840 possible kinds of autocracy.CHECK, contact Milan.}

6.1.3 Israel and the Palestinians
7 Bridge sampler estimates of the log marginal data densities
<table>
<thead>
<tr>
<th>(Sub) Genre</th>
<th>Key Concepts</th>
<th>Representative Works</th>
</tr>
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<tbody>
<tr>
<td>RATIONALIST</td>
<td>Mispresentation of preferences; commitment mechanism divisibility of issues</td>
<td>Fearon (1995)</td>
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<tr>
<td>Two-level (dynamic)</td>
<td>accountability; credibility</td>
<td>Brandt et al. (2008)</td>
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<tr>
<td>MACRO-DYADIC</td>
<td>enduring vs. strategic rivalry; rivalry dynamics</td>
<td>Diehl and Goertz (2000); Colaresi et al. (2008)</td>
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<tr>
<td>Theories of Rivalry</td>
<td>Trade-conflict trade composition; inter vs. intra industry trade</td>
<td>Li &amp; Reuveny (2011) Peterson &amp; Theis (2011)</td>
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<tr>
<td>Democratic Peace &amp; Democratization</td>
<td>nationalist prestige strategies</td>
<td>Numerous Examples Mansfield and Snyder (1995)</td>
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Table 3: The Study of Intra and Interstate Conflict
Figure 17: Polity Scores for Israel, 1945-2010. Source: Polity Website; www.systemicpeace.org

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Table 4: Log marginal data density for the Levant dataset

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Table 5: Log marginal data density for the Cross-Straits dataset
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Table 6: Log marginal data density for the Indian Subcontinent dataset