

Hostage Taking: Understanding Terrorism Event Dynamics

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Abstract

This paper employs advanced time series methods to identify the dynamic properties of three hostage taking series. The immediate and long run multipliers of three covariates — successful past negotiations, violent ends, and deaths — are identified. Each hostage series responds differently to the covariates. Past concessions have the strongest impact on generating future kidnapping events, supporting the conventional wisdom to abide by a stated no-concession policy. Each hostage series has different changepoints caused by a variety of circumstances. Skyjackings and kidnappings are negatively correlated, while skyjackings and other hostage events are positively correlated. Policy recommendations are offered.

JEL classification: C22; D74; H56

Key words: Kidnappings, Skyjackings, No-concession policy, Impact multipliers, Poisson autoregressive model, Changepoint models, reversible-jump Markov chain Monte Carlo methods

1. Introduction

From the seizure of the Israeli athletes during the 1972 Munich Olympics to the four simultaneous skyjackings on September 11, 2001 (henceforth, 9/11), hostage events have been some of the most spectacular and newsworthy attacks during the modern era of

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international terrorism. In fact, this modern era is traced to the July 22, 1968 hijacking of an Israeli El Al flight by the Popular Front for the Liberation of Palestine (PFLP) (Hoffman, 2006). During the incident, the PFLP terrorists gained significant media coverage and forced the Israelis to negotiate with the Palestinians (Hoffman, 1998, 68). After the incident, terrorists increasingly staged attacks at foreign venues to capture the world's attention. Other high-profile hostage events include: the PFLP's abduction of eleven Organization of Petroleum Exporting Countries (OPEC) ministers on December 21, 1975; the students' takeover of the U.S. embassy in Tehran, Iran on November 4, 1979; and the Chechen rebels' seizure of over a thousand hostages at a middle school in Beslan, Russia on September 1, 2004.

Terrorist hostage incidents fall into four categories: kidnappings, skyjackings, barricade and hostage taking missions (i.e., the takeover of a building with hostages), and the capture of a nonaerial means of transportation (e.g., a boat, train, or bus). Kidnappings are the least risky hostage events owing to their unknown location and, as such, account for over two-thirds of the hostage incidents (1318 of 1941 incidents in our data set). Skyjackings are less risky than barricade and hostage taking missions and other forms of hijackings, since it is more difficult for authorities to approach a plane unseen than to approach buildings or other means of transport. Terrorists engage more often in skyjackings than in other forms of nonkidnapping hostage events (see below). Even though hostage taking incidents are among some of the most dangerous missions, terrorists resort to such attacks because they can result in high payoffs in terms of publicity, recruitment, and ransoms. Hostage events comprise 15% of all terrorist events for the 1968-2005 sample period (Mickolus et al., 2006). Terrorists choose their mix of attacks according to perceived risks, engaging in riskier modes less often (Sandler et al., 1983), which is borne out by the frequency of the four kinds of hostage missions.

For hostage events, the conventional wisdom is that past concessions to terrorists encourage additional seizures owing to terrorists' updated priors of high payoffs. If, instead, terrorists know beforehand that they have nothing to gain from hostage taking due to a government's announced no-concession stance, then they will never abduct hostages. Thus, many governments — including the United States — have adopted a no-concession policy in the hopes of reducing hostage taking (U.S. Department of State, 2003). Lapan and Sandler (1988), however, demonstrate that the efficacy of the no-concession stance hinges on some unstated assumptions, which often do not hold (e.g., credibility of the government's pledge and the absence of terrorist gains from a negotiation failure). Terrorists believe that, if they capture a sufficiently valuable hostage, the government will renege on its no-concession pledge. There have been many instances of this in the past—e.g., a large ransom was paid to the PFLP for the release of the OPEC ministers in 1975—that foster this belief. Each concession made to hostage taking terrorists by one government makes the terrorists change their beliefs about the likelihood of other governments' giving into their demands. For example, the Reagan administration's arms-for-hostages deal to release Rev. Benjamin Weir, Rev. Lawrence Jenco, and David Jacobsen encouraged the terrorists to capture other academics and journalists in Beirut (e.g., Robert Polhill, Allan Steen, Jesse Turner, Mithileshwar Singh, and Roger Augue) to replace those released (Enders & Sandler, 2006, 172–173). In 2004, terrorists in Iraq took other countries' citizens hostage once South Korea and the Philippines made concessions. Apparently, one country's concession causes a negative influence or externality on the perceived credibility of other target countries' pledges. Although the influence of past concessions on generat-

ing future hostage incidents is an important policy question, the essential no-concession wisdom has never been tested empirically.

There has also been no dynamic test of whether the use of force to end a hostage mission discourages future incidents, thereby justifying the associated loss of life including that of some of the hostages. Up until now, there has not been a sufficiently long time series of hostage events to test important dynamic propositions including how policy statements and past actions generate or discourage future hostage incidents. In addition, advanced time series methods have not been applied to disaggregated hostage events to identify important changepoints resulting from policies and/or exogenous shocks.

This paper has a number of purposes. First, it employs sophisticated time series techniques to quantify how past concessions encourage future hostage events; similarly, it applies these methods to quantify how violent actions (e.g., the authorities storming a hijacked plane) influence future hostage missions. Second, we use advanced methods to identify past changepoints in the hostage taking series where the arrival rates increase or decrease. Once these changepoints are identified, we can match them, in most cases, with the precipitating shock or event. By using only exogenously given policy interventions, past analyses miss many changepoints. Third, we ascertain how hostage events differ when the location is unknown or known. If, for example, the dynamics associated with kidnappings (unknown location) differs from that of other kinds of hostage events, then policy recommendations must also differ between types of hostage events. Fourth, we determine the temporal level of aggregation (i.e., days, months, or quarters) or the unit of analysis that is most appropriate.

In the course of the study, we establish significant empirical support for the conventional wisdom with respect to maintaining a no-concession policy. For kidnappings, each concession to the terrorists results in two to three additional abductions. A smaller number of additional skyjackings and other hostage incidents follows concessions granted. Unexpectedly, violent ends or deaths are associated in many instances with more, not fewer, hostage incidents. Thus, decisive actions by the authorities to end a hostage event with force did not always deter future actions, except for skyjackings. The level of aggregation can make a difference in identifying the impact of these covariates. Moreover, alternative types of hostage events are associated with different changepoints. The estimated arrival rates of kidnappings and skyjackings are negatively correlated, indicative of substitution effects; the arrival rates of kidnappings and nonskyjacking hostage events are uncorrelated; and the arrival rates of skyjackings and nonkidnapping hostage events are positively correlated, indicative of complementarity.

The body of the paper contains four sections. Section 2 presents preliminaries including essential definitions, concepts, and brief review of the relevant literature. The data is discussed in Section 3. This is followed by the empirical analysis in Section 4. The final section contains concluding remarks and further policy implications.

2. Preliminaries

Terrorism is the premeditated use or threat to use violence by individuals or subnational groups against noncombatants to obtain political or social objectives through the intimidation of a large audience, beyond that of the immediate victims. In this definition, two crucial ingredients are violence and the political/social motive; violent acts without

such motives are merely criminal acts and do not constitute terrorism. Other essential aspects of terrorism that have been subject to debate concern the identity of the victim (i.e., noncombatant or otherwise), perpetrator (e.g., states as terrorists), and audience (Hoffman, 1998; Enders & Sandler, 2006). Our definition is closely akin to that of the U.S. Department of State (2003) and captures many features of the myriad definitions in the literature. Moreover, this definition is consistent with that of the data set described in the next section. Terrorists utilize different modes of attack — e.g., bombings, assassinations, armed attacks, skyjackings, kidnappings, and barricade missions — to pressure a government into conceding to their political demands. Our focus is on hostage events since we are interested in how past concessions or violent actions by governments influence the arrival rate of future incidents. Such a study informs governments as to whether their independent policy responses work to curtail or encourage future hostage taking incidents. The analysis here assists governments learn best practices.

Terrorism is further subdivided into domestic and transnational events. Domestic terrorism is homegrown (i.e., home financed, planned, and executed) and has consequences for just the host country, its institutions, citizens, property, and policies. The kidnapping of a German industrialist, Hanns Martin Schleyer, in 1977 by the Red Army Faction is a domestic terrorist incident. In contrast, transnational terrorism involves perpetrators, victims, institutions, governments, or citizens from at least two countries. Incidents funded or planned abroad are transnational terrorist events, as are incidents where the terrorists cross a national border to engage in the attack. The January 2002 kidnapping of *Wall Street Journal* reporter Daniel Pearl in Pakistan is a transnational terrorist event. A skyjacking of a plane that originates in Rome and is made to fly to Beirut is a transnational incident. The kidnappings of Westerners and other foreign nationals in Lebanon during the 1980s, as well as the kidnappings of foreign contractors and aid workers in Iraq following the Abu Ghraib prison scandal on April 6, 2004, are examples of transnational hostage missions. The four simultaneous skyjackings on 9/11 are transnational because the hijackers were foreigners, the victims came from many countries, and the financial implications were global. In general, transnational terrorist incidents have ramifications that transcend the host country's soil.

The past literature on terrorist hostage taking includes both theoretical and empirical contributions. The theoretical literature is primarily interested in the desirability (Islam & Shahin, 1989) and the practicality (Lapan & Sandler, 1988) of the no-concession policy in discouraging future hostage taking. These papers provide some casual evidence, but do not present any empirical test of the propositions put forward. The empirical literature focuses on the effectiveness of metal detectors in airports and other counterterrorism policies (e.g., sky marshals, UN conventions outlawing skyjackings, and longer jail sentences to convicted skyjackers) to inhibit subsequent skyjackings (Enders & Sandler, 1993; Enders et al., 1990a,b; Landes, 1978). These past studies prespecify the changepoints in hostage events rather than allow the data to uncover them. Moreover, the dependent variable — say, the number of skyjackings — were not related to covariates about the (past) events, such as past concessions. Another set of articles investigates the determinants of hostage taking success (Gaibulloev & Sandler, 2009; Sandler & Scott, 1987) and bargaining aspects (Atkinson et al., 1987). Like this study, Poe (1988) examines whether a tough stance against hostage takers limits future abductions. This earlier study uses multiple regression and cannot capture the true dynamics of past hostage taking incidents, in contrast to the Poisson autoregressive and changepoint models in this paper.

Poe finds that a tough stance did not deter future hostage missions.

In a recent paper, Enders & Sandler (2005) examine prespecified (e.g., 9/11) and unspecified changepoints in hostage events time series. Unlike the current study, which disaggregates hostage incidents into three distinct classes, Enders & Sandler (2005) aggregate all hostage events to quarterly series. These authors apply Bai-Perron (1998, 2003) methods rather than the changepoint models employed here. In this study, we identify a much richer set of changepoints that differ among alternative hostage missions.

Finally, Lee et al. (2008) use an alternative estimation method (sequential importance sampling) rather than a reversible jump Markov chain Monte Carlo method, but apply it to nonhostage incidents for a truncated time period that ends prior to 9/11. Like the current study, these authors use monthly data. Their main concern is whether past patterns in the data could have predicted 9/11.

3. Data

We use event data on terrorist hostage incidents drawn from International Terrorism: Attributes of Terrorist Events (ITERATE), which was originally devised by Mickolus (1982) and later updated by Mickolus et al. (2006). ITERATE records just transnational terrorist incidents using a host of sources, including the Associated Press, United Press International, Reuters tickers, *New York Times*, *Washington Post*, the *Foreign Broadcast Information Services (FBIS) Daily Reports*, ABC, NBC, and CBS evening news. Through 1996, the regional *FBIS Daily Reports* have been invaluable: these reports draw from hundreds of world print and electronic media services and are the most complete source for foreign coverage of terrorist incidents. ITERATE currently includes 12,942 terrorism incidents from 1968 to 2005. An overlap of coders ensures a consistency of coding as the data are updated.

ITERATE's COMMON file records a host of general observations about each terrorist event including the incident date, incident type, and the total number of individuals (i.e., terrorists, victims, or bystanders) killed. In addition, ITERATE's HOSTAGE file, which has been recently updated to run from 1968 to 2005, includes a negotiation success variable that indicates whether the terrorists received none, some, or all of their demands. The HOSTAGE file also includes the response of the target — shoot-out with terrorists or something else (e.g., capitulation, Bangkok solution [i.e., a plane to a safe haven], no compromise, or no shoot-out). These two variables allow us to construct two important covariates. We have merged the hostage events with those in the COMMON file so that we have common and hostage attributes of 1941 hostage events, made up of 1318 kidnappings, 380 skyjackings, and 243 other hostage events (i.e., barricade missions and nonaerial hijackings).¹ For hostage events without a fully specified date (either missing a month or a day), events were assigned a modal date. Missing days were assigned the 15th of the month (if a month were supplied) and missing months were assigned to June. All observations with a missing month have a missing day. Using this data, we constructed

¹ These are ITERATE incident types 1 (kidnapping), 2 (barricade and hostage seizure), 9 (aerial hijacking) and 10 (takeover of nonaerial means of transportation).

three time series — a KIDNAP series, a SKYJACK series, and an OTHER hostage events series (known henceforth as OTHER) for the 1968-2005 period.²

Figure 1 presents the KIDNAP time series and their autocorrelation functions at monthly and quarterly levels of aggregation. The dashed vertical line in each graph is for 9/11. Visual inspection of these series reveal two immediate properties: 1) the series are cyclical (around an AR(1-4) processes depending on the level of aggregation), and 2) the variance of the series increases over time. The latter property is especially evident in the quarterly data. The right column in Figure 1 are the autocorrelation functions for the three series.³ Time scales in these ACFs are based on the periodicity of the data, so the “1” on the x -axis in the monthly data is 12 months, and 4 quarters in the quarterly data. The y -axis are the autocorrelations.

Figures 2 and 3 present the same information as Figure 1 for the SKYJACK, and OTHER series. Note that the SKYJACK and OTHER series appear to have negative trends, descending from high points in the 1980s and 1990s. The KIDNAP event series display higher volatility in more recent periods, particularly post 9/11 where the series reaches its historical maximum. An upward trend since 1990 is evident for the quarterly KIDNAP series, except for a drop prior to 9/11.

4. Testing for cycles and changes in hostage taking events

We are particularly interested in two questions about hostage events: are they cyclical and have there been structural changes in the hostage taking series. The former are motivated by previous findings such as Enders & Sandler (2005) where hostage taking events are shown to be both cyclical and subject to structural shifts. However, these earlier analyses can be refined by careful modeling of the KIDNAP, SKYJACK and OTHER series. In the literature, cycles are attributed to a cat-and-mouse game between the authorities and the terrorists as defensive breakthroughs (e.g., metal detectors at airports) are countered by operational innovations (e.g., plastic guns or flammable liquids). In other cases, cycles may stem from demonstration effects of success or failure (see Enders & Sandler, 2006, 2005; Enders et al., 1992; Im et al., 1987). Whatever their cause, we must account for cycles and structural breaks to identify the true dynamics of the time series.

The refinements we employ here are threefold. First, we work with more disaggregated data (also see Barros & Gil-Alana, 2006). This is important since 1) aggregating to quarterly data can mask cyclical components (at frequencies less than a quarter), and 2) may confound inferences about structural shifts since they may be “lost” in a quarter. Second, we employ event count time series methods rather than ARIMA or (normal) linear regression models. Event count models based on Poisson and negative binomial

² These data are sparse. For the January 1, 1968 to December 31, 2005 period, 8.6% of the days have one or more KIDNAP event, 2.6% of the days have one or more SKYJACK event, and 1.7% of the days have one or more OTHER event. For a monthly aggregation of the data, 85% of the months have some KIDNAP events, 47% of the months have some SKYJACK events, and 35% of the months have an OTHER event.

³ These ACFs are computed using the standardized hostage counts. They are computed using $z_t = \frac{y_t - \bar{y}}{\sigma}$ where \bar{y} and σ are the mean and standard deviation, respectively of the series. This method is suggested by Cameron & Trivedi (1998).

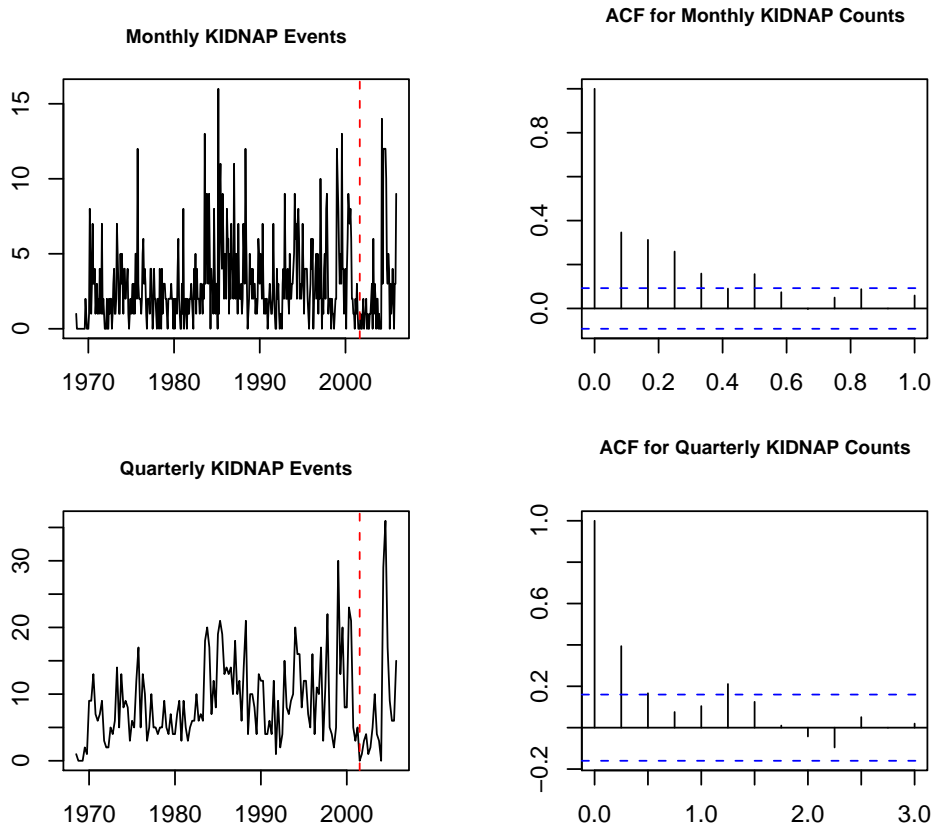


Fig. 1. ITERATE KIDNAP events time series, 1968–2005.

data generation processes provide less biased and more consistent estimates of cyclical and structural components for data like those presented here. Brandt et al. (2000), Brandt & Williams (2001) and Park (2007) all present models for count data that produce less biased inferences about cyclical components and structural shifts. This is important, since incorrect data generation process assumptions will potentially invalidate tests for cycles and shifts. Finally, we employ more robust methods for checking for structural changes in the disaggregated data. Such methods check for possibly incorrect assumptions about the number and timing of structural breaks in the three hostage (event count) series. The methods used here — event count time series regressions and a Bayesian reversible-jump changepoint model — allows us to combine prior beliefs about the number of changepoints and the data to produce robust inferences about changepoints, without indefensible data aggregation or exogenously limiting the number of changepoints in the data (see, e.g., Barros, 2003; Barros & Gil-Alana, 2006; Enders et al., 1990a,b). The remainder of this section presents two alternative models of the three hostage event series.

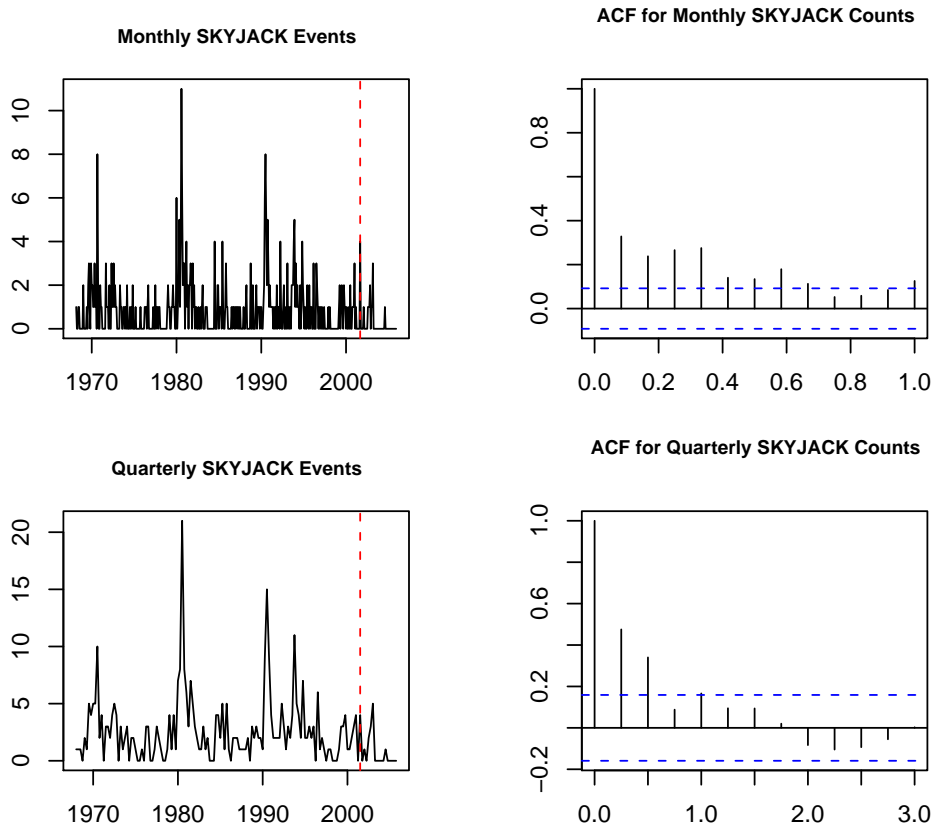


Fig. 2. ITERATE SKYJACK events time series, 1968–2005.

4.1. $PAR(p)$ analyses

One can look at the cyclical properties of the data using the Poisson autoregressive model ($PAR(p)$) of Brandt & Williams (2001). This model is based on an extended Kalman filter for the count process. Let y_t be the observed number of hostage events at time t , and x_t be a $1 \times k$ vector of covariates. The basic model for the counts has two equations, a measurement equation and a transition equation that describe the evolution of the counts via an autoregressive process and some initial conditions:

Measurement equation:

$$\Pr(y_t | m_t) = \frac{m_t^{y_t} \exp(-m_t)}{y_t!}$$

Transition Equation:

$$m_t = \sum_{i=1}^p \rho_i y_{t-i} + \left(1 - \sum_{i=1}^p \rho_i\right) \exp(x_t \beta)$$

Initial Conditions:

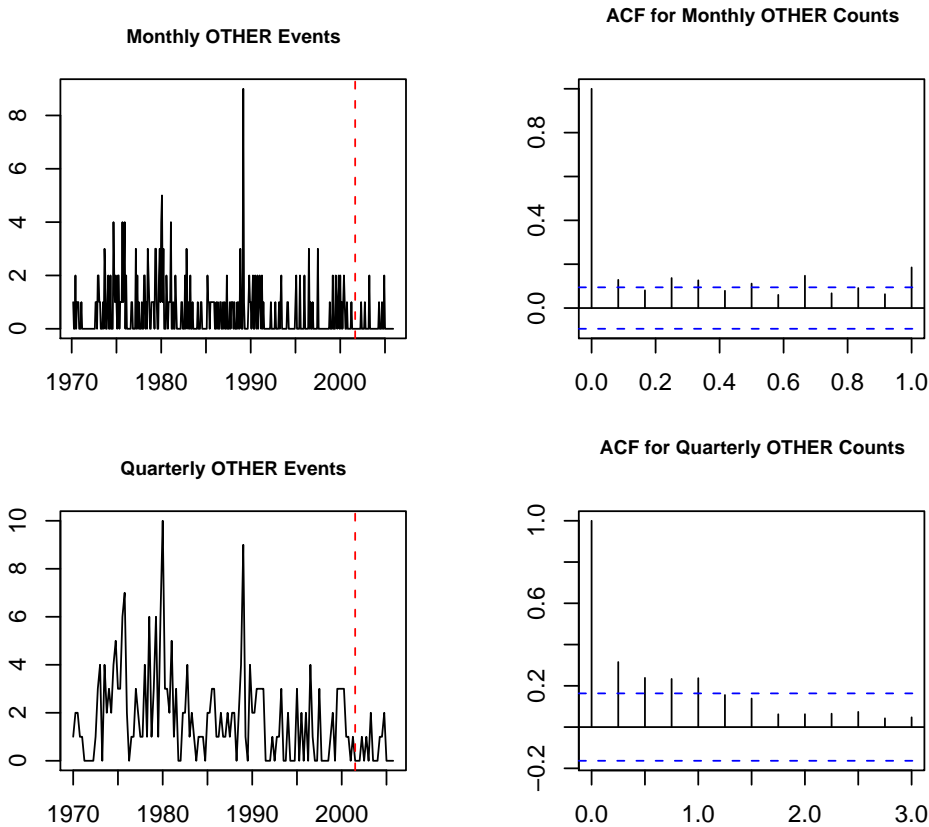


Fig. 3. ITERATE OTHER events time series, 1968–2005.

$$\Pr(m_t | y_{t-1}, \dots, y_{t-p}) = \Gamma(\sigma_{t-1} m_{t-1}, \sigma_{t-1})$$

where m_t is the mean of the Poisson process at time t , ρ_i 's are the autoregressive parameters for the lagged counts, β is a $k \times 1$ vector of regression coefficients for the covariates, and σ_t is the scale of the transition equation at time t . The measurement equation is a Poisson density for the number of events y_t at time t , while the transition equation describes how the (latent) mean number of events evolves via an autoregressive process. The initial conditions determine the probability density for the autoregressive process in each time period, whose mean is gamma distributed with a scale parameter of σ_t . The resulting predictive distribution of the counts is a negative binomial (for details see Brandt & Williams, 2001), which accounts for the overdispersion of the data due to the serial correlation in the counts.

The analysis here includes three covariates for each of hostage series. The first covariate indicates past negotiation success of the hostage missions, in which the terrorists obtain some or all of their demands. Because terrorists are apt to ask for as much as possible to maximize concessions paid, gaining their full demands is too stringent a condition for negotiation success. Based on conventional wisdom (previously discussed), successful negotiations in one type of hostage incident is likely to generate more incidents of the

same type as terrorists raise their priors for expected gains. From the HOSTAGE file, the negotiation success covariate is coded as 1 if the terrorists received some or all of their demand and 0 otherwise. The second covariate derives from the “response of the target” from the HOSTAGE file of ITERATE, where the constructed variable of a violent end is coded as 1 for “shoot out with terrorists” and 0 otherwise. We anticipate that such a forceful end to an incident will deter future incidents of that type unless the terrorists are motivated by martyrdom or publicity. The third covariate is from the COMMON file of ITERATE and indicates whether deaths are associated with a hostage incident. Incidents with one or more deaths are coded as 1 and those with no deaths are coded as 0. Such bloodshed is anticipated to deter future incidents of that type unless the perpetrators are more bent on murder than on other gains. All three covariants are recorded as within-period sums of the relevant variable for the specific kind of hostage event.

There are two issues that must be addressed in specifying the PAR(p) model with these covariates. The first is the number of lags of the count series in the model. We fit a series of these PAR(p) models for each of the three hostage time series. In so doing, we tested for the lag length of each PAR model using successive models with higher lags and selected the most parsimonious model with statistically significant lag coefficients. The second issue is the distributed lag specification for the exogenous variables. We looked at models with contemporaneous covariates and lags up to two periods. Based on hypothesis tests and Akaike information criteria (AIC) values, we selected the most parsimonious distributed lag specification. Table 1 summarizes the results of the models for both quarterly and monthly aggregations of the data.⁴

These results generate four main insights into the hostage data. First, the hostage events are not independent of each other. The joint hypothesis for $\rho_i = 0, i = 1, \dots, p$ for the PAR(p) is a test of whether the autoregressive process is jointly zero and the data are better explained by a Poisson regression, where the hostage events are independent of each other. This test is rejected for each of the models. Thus, there is a dependent, autoregressive process among the hostage events in each time series. Second, this temporal dependence among the series is generally positive, which means that hostage taking events generally are correlated positively over time. Third, the equilibration of additional new hostage events is rather rapid, since the sum of the AR coefficients tends to be bounded away from 1. This is interpreted as meaning that the impact of each hostage taking event on subsequent events occurs over a short period of time (approximately 8-12 months at most). Finally, negotiation successes, violent endings, and incidents with deaths have statistically significant effects in predicting each of the hostage series. This last conclusion is based on the statistically significant covariates in the latter rows of the table. The positive influence of negotiation success agrees with our priors, while the positive influence of violent end and deaths does not agree with our priors, except when martyrdom or publicity are motivators. By calculating the multipliers for each covariate for each of the three series, we are better able to quantify their impacts.

This latter result can be seen by computing the impact and long run multipliers of a one unit change in each of the covariates (holding the others at their means). These are found by the following (see Brandt and Williams 2001 for details):

⁴ There are fewer observations in some of the series because the PAR(p) model cannot be estimated with initial observations of zero. Truncating the data series to the first nonzero observation produces the smaller samples.

Table 1. PAR(p) results for monthly and quarterly KIDNAP, SKYJACK and OTHER series 1968–2005.

Parameters	KIDNAP		SKYJACK		OTHER	
	Monthly	Quarterly	Monthly	Quarterly	Monthly	Quarterly
ρ_1	0.23 (0.04)	0.18 (0.05)	0.25 (0.07)	0.30 (0.07)	0.19 (0.05)	0.21 (0.09)
ρ_2	0.13 (0.05)	0.14 (0.05)	0.17 (0.08)	0.16 (0.08)		
ρ_3	0.02 (0.04)		0.06 (0.07)	-0.13 (0.05)		
ρ_4	-0.02 (0.04)		0.13 (0.07)	0.11 (0.06)		
ρ_5	0.002 (0.04)					
ρ_6	0.12 (0.04)					
ρ_7	0.03 (0.04)					
ρ_8	-0.12 (0.04)					
Negotiation Success $_t$	0.27 (0.06)	0.22 (0.04)	0.67 (0.07)	0.33 (0.06)	0.34 (0.19)	0.43 (0.15)
Negotiation Success $_{t-1}$		0.12 (0.04)				-0.42 (0.24)
Violent End $_t$	0.37 (0.06)	0.24 (0.05)	0.87 (0.14)	-0.16 (0.16)	0.66 (0.16)	0.07 (0.20)
Violent End $_{t-1}$		-0.08 (0.06)				0.53 (0.20)
Incidents with Deaths $_t$	0.36 (0.04)	0.16 (0.02)	0.87 (0.09)	0.53 (0.10)	0.93 (0.14)	0.52 (0.13)
Incidents with Deaths $_{t-1}$		-0.10 (0.03)				-0.26 (0.18)
Intercept	0.73 (0.07)	1.65 (0.08)	-0.52 (0.16)	0.20 (0.18)	-0.83 (0.11)	0.06 (0.13)
Log likelihood	-862	-405	-503	-265	-399	-218
AIC	1747	827	1019	544	806	450
χ^2, H_0 : Poisson model (p-value)	107 (<0.01)	29 (<0.01)	98 (<0.01)	51 (<0.01)	13 (<0.01)	6 (0.02)
d.f.	437	140	446	144	425	135

Note: Standard errors are in parentheses. The ρ_i terms are the autoregressive lag coefficients at lag i . All of the Wald tests for a reduction to a Poisson model have p degrees of freedom (the number of lagged counts) and have p -values generally less than 0.01.

$$\text{Impact multiplier : } \left(1 - \sum_{i=1}^p \rho_i \right) \exp(\gamma z_t + \beta_1 x_t + \beta_2 x_{t-1}) \beta_1$$

$$\text{Long run multiplier : } \exp(\gamma z_t + \beta_1 x_t + \beta_2 x_{t-1}) (\beta_1 + \beta_2)$$

where β_i and γ are a partition of the coefficients, x_{t-i} are a given shock to exogenous variables and z_t are the fixed variables (typically held at their sample means). The impact multiplier finds the instantaneous effect of a one unit change in an x_t variable at time $t+1$. The total multiplier computes the total effect of the one unit change in the covariate. Tables 2 and 3 show the computed multipliers as well as a Monte Carlo estimate of their 68% confidence regions (approximately one standard deviation around the mean). These multipliers show the impact or change in the KIDNAP, SKYJACK, or OTHER series for a one unit changes in one of the independent variables (specified in the columns) holding all of the other variables at their sample means. The first rows in each table give the impact (next month or quarter) effect, while the final rows give the total impact.

A comparison of the two tables shows that the level of data aggregation makes a difference in subsequent conclusions. For the monthly data, the effects of one more negotiation success, violent end, or deaths incident are more hostage events. For the monthly KIDNAP series, the impact of a negotiation success, violent end, or deaths incident is 0.44 to 0.61 new kidnappings. The total (long run) impacts of one more negotiation success, violent end, or deaths incident on KIDNAP is 0.75 to 1.03 new kidnappings. In the case of SKYJACK, the three covariates are associated with much weaker impacts that vary between 0.21 and 0.28 new incidents for the immediate effect and between 0.56 and 0.73 new incidents for the total impact. Compared with the KIDNAP series, OTHER hostage events also display smaller impact and total multipliers. Generally, we see that an unknown location for hostage incidents means that the covariates, such as negotiation success, have a greater impact initially and over time than for known locations. This implies that the no-concession policy is particularly important for kidnappings, which will also be borne out for quarterly data. For all monthly hostage series, the effect of the three covariates is to raise hostage events.

The quarterly data PAR(p) multipliers are given in Table 3 and differ from the monthly results. For the quarterly data, a one unit increase in each of the covariates has a positive effect on KIDNAP. These results are approximately two to three times the monthly effects of the covariates for four of the six multipliers. These multiples are consistent with the quarterly data aggregation. Most notable, conceding to kidnappers' demands is associated with 2.62 additional abductions, lending strong support for the conventional wisdom. Neither violent ends nor deaths during the incident are a deterrent to kidnappings, probably because hostage takers believe that better efforts to keep their location unknown will not result in a shoot-out with authorities even if a recent incident concluded this way. Past violence in kidnappings may encourage future events owing to the promise of increased media coverage. Moreover, deaths of a hostage may still result in a ransom, provided that the death is discovered after payment. The quarterly SKYJACK multipliers associated with negotiation success and deaths are positive and somewhat larger than their monthly counterparts. These slightly larger multipliers are not consistent with the quarterly data aggregation. For quarterly data, a violent end deters future skyjackings immediately and in the long run. Although this influence is not large, it greatly differs from the monthly data and supports past actions to end a skyjacking forcefully (e.g.,

Table 2. Impact and long run impact multipliers for one unit increases in each of the independent variables for the monthly PAR(p) models.

	KIDNAP			SKYJACK			OTHER		
	Negotiation Success	Violent End	Incidents with Deaths	Negotiation Success	Violent End	Incidents with Deaths	Negotiation Success	Violent End	Incidents with Deaths
Impact	0.44	0.61	0.58	0.21	0.28	0.28	0.15	0.29	0.41
	(0.33, 0.55)	(0.51, 0.71)	(0.52, 0.65)	(0.18, 0.25)	(0.23, 0.33)	(0.24, 0.32)	(0.07, 0.23)	(0.22, 0.36)	(0.34, 0.48)
Total	0.75	1.03	0.99	0.56	0.72	0.73	0.19	0.36	0.51
	(0.57, 0.93)	(0.87, 1.20)	(0.90, 1.09)	(0.47, 0.65)	(0.61, 0.84)	(0.63, 0.84)	(0.08, 0.29)	(0.27, 0.45)	(0.44, 0.59)

Note: The 68% confidence regions included in parentheses under each multiplier.

Table 3. Impact and long run impact multipliers for one unit increases in each of the independent variables for the quarterly PAR(p) models.

	KIDNAP			SKYJACK			OTHER		
	Negotiation Success	Violent End	Incidents with Deaths	Negotiation Success	Violent End	Incidents with Deaths	Negotiation Success	Violent End	Incidents with Deaths
Impact	1.15	1.20	0.84	0.33	-0.16	0.53	0.48	0.09	0.59
	(0.97, 1.33)	(1.00, 1.41)	(0.75, 0.94)	(0.27, 0.39)	(-0.31, -0.01)	(0.43, 0.63)	(0.33, 0.62)	(-0.14, 0.31)	(0.44, 0.73)
Total	2.62	1.18	0.47	0.59	-0.29	0.96	0.01	0.87	0.37
	(2.19, 3.06)	(0.72, 1.65)	(0.27, 0.67)	(0.49, 0.69)	(-0.57, -0.02)	(0.81, 1.11)	(-0.32, 0.34)	(0.45, 1.30)	(0.04, 0.70)

Note: The 68% confidence regions included in parentheses under each multiplier.

Operation Thunderbolt by Israeli commandos at Entebbe Airport in Uganda to free the hostages from Air France flight 139 in June 1976). Data aggregation also makes a difference for OTHER hostage events, where instead of the net positive multipliers of the monthly data, the quarterly data’s impact and long run multipliers are more complex when the confidence intervals are consulted. The total multiplier is nonzero for only the violent end and death covariates; thus, the immediate impact of negotiation success on OTHER events is ameliorated in the long run.

In sum, we find that negotiation success generates more kidnappings regardless of the unit of analysis. Moreover, kidnappings with violent ends or deaths do not deter future incidents. When examined quarterly, violent ends deter skyjackings but deaths do not. The latter finding is likely due to past events where the skyjackers murdered a passenger — e.g., TWA flight 847 on June 14, 1985 — to make the authorities take their demands seriously. Such tactics were often associated with concessions eventually being made. For OTHER hostage events, the three covariates generally resulted in more hostage taking. The magnitude and, for skyjackings, the direction of the covariate’s influence is time-frame dependent.

One reason for the differing results for the monthly versus quarterly data is that there may be structural changes in the three hostage series. The next section looks at this possibility.

4.2. Bayesian multiple changepoint model analysis

The PAR(p) models assume that the data have a unique equilibrium, which is violated if there are structural changes in the number of average events per period or a nonindependent arrival time between hostage events. This could be the result of the data being better explained by a clustered or time-dependent Poisson process, such as a negative binomial process. In fact, the PAR(p) models results show that the predictive distribution for this model is a negative binomial.

The PAR(p) model does not allow one to test for the presence of structural changes in the inter-arrival times of hostage events. One could do this by fitting a sequence of models and using tests analogous to those for structural breaks in regression models. Such a task, however, requires the analyst to know or specify the number and timing of the possible structural breaks. This would be an *ad hoc* task and is largely self-fulfilling because of analysts’ biases in looking for or “confirming” changes (cf., Park, 2007).

Alternatively, one could use a Bai-Perron test for structural breaks. But this test depends on an assumption that the data are normally distributed, which is not the case for event count data at low frequencies unless the mean number of counts is “large.” Thus, we adopt a different model that uses a multiple changepoint model, which looks for changes in the arrival of events in a Poisson process. The assumption here is that each *individual* event is a draw from a cumulative counting process where the timing between the events is a time-dependent rate.⁵ The model is referred to as “multiple” changepoint model because it allows for an endogenous set of changes or shifts to occur in the rate of events. At each point in time one evaluates whether there should be a changepoint to a new level (a birth) or a changepoint back to a previous level (a death), a change in the

⁵ Such models are commonly used to model disasters, such as coal mining accidents (Raftery & Akman, 1986; Green, 1995).

height or probability of each changepoint, or a change in the location of the position of a changepoint. For these four options, one estimates the endogenously determined number of breaks or shifts in the arrival rate. These shifts can be to higher or lower hostage event arrival rates. This procedure surmounts the problem of pre-specifying the changepoints and biasing the results.

An additional complication with specifying a multiple changepoint model for frequentist inference is that an analyst would need to pre-specify the maximal number of breaks. Since *a priori* the number of changepoints is unknown, one must find a robust method for evaluating whether to add or eliminate a changepoint from the model. This problem has been solved in a Bayesian approach by the development of *reversible jump Markov chain Monte Carlo* (RJ-MCMC) methods. These methods allow one to sample whether the posterior distribution of the data (and parameters) are better characterized by a model with either $k - 1$, k , or $k + 1$ changepoints. The choice of the value of k is a model determination or order issue: the choice of k determines the number of parameters in the model.

The Bayesian model for the changepoints is provided by Green (1995). The model uses daily data on the hostage events, since any aggregation of the data would only rescale the arrival rate of the events by the periodicity of the data. Thus, for determining breaks, the level of aggregation often has little consequence. Let the data points for the Poisson process of number of hostage events per day be $y_i, i = 1, 2, \dots, n \in [0, L]$. The daily *arrival rate* for the Poisson process for the events varies over time according to the arrival rate function $w(t)$. The likelihood for these Poisson events is

$$\sum_{i=1}^n \log\{w(y_i)\} - \int_0^L w(t)dt$$

where n is the number of events and L is the total elapsed days of the hostage events. The multiple changepoint aspect enters the model by assuming there are step functions that describe the jumps in the rate function $w(t)$. Suppose there are k steps at intervals $0 < s_1 < s_2 < \dots < s_k < L$ and the steps take a value or height of h_j between $[s_j, s_{j+1}]$ for $j = 0, 1, 2, \dots, k$. The number of possible steps is assumed to be Poisson distributed with

$$p(k) = \exp(-\lambda) \frac{\lambda^k}{k!},$$

where $k \leq k_{max}$ and k_{max} is the arbitrary maximum number of breaks. Under these assumptions, the steps are even-numbered order statistics from $2k + 1$ points over a uniform interval $[0, L]$. The heights of the steps, h_0, h_1, \dots, h_k (which describe the density of changepoints) are independent draws from a $\Gamma(\alpha, \beta)$ density. These assumptions define a model where up to k_{max} breaks are possible, with a uniform density for the break locations. The latter is computationally expensive and possibly leads to selecting too many breaks.

This model could be implemented by classical (i.e., maximum likelihood) methods if one were to pre-specify k , but this presupposes knowing the number of changepoints. One instead can take a Bayesian approach and condition the model on the choice of k , which requires comparing the posterior probability of adding or subtracting from k . This is the “reversible” part of the estimation since it changes the dimension of the

number of changepoints in $w(\cdot)$ from either 1) k to $k - 1$ (a death step), 2) k to $k + 1$ (a birth step), 3) changing the step height, or 4) changing the position of a step. In this situation, classical likelihood theory breaks down because the changepoint models for k versus $k \pm 1$ are nonnested, but Bayesian estimation (even with a diffuse prior about the number of changepoints and their arrival times) provides a solid basis for inference (see Green, 1995).

Bayesian RJ-MCMC changepoint models for the daily KIDNAP, SKYJACK, and OTHER series were fitted with a diffuse prior.⁶ The RJ-MCMC sampler consisted of 400,000 burn-in iterations (which were discarded to remove the initial conditions from the sampler) and a final posterior sample of one million draws, which were thinned from a total of twenty million draws from the posterior density.⁷

Figure 4 shows the plot of the cumulative number of events, the arrival rate of new events and the changepoints in the KIDNAP series, while Table 4 shows the ten estimated breaks in the KIDNAP series. The solid line in the figure is the cumulative number of KIDNAP events over the period while the dashed line is the estimated arrival rate of new events. Changes in the slope of the arrival rate are identified as the changepoints which are presented in Table 4. The table's columns display the median date for the changepoints, their 68% credible intervals, and the direction of change. In the right-most column of Table 4, we have matched, based on detailed historical accounts (e.g., U.S. Department of State, various years and ITERATE writeups), the precipitating events. Thus, changepoint 1 is attributed to the rise in transnational terrorism that followed Israeli occupation after the Arab-Israeli wars. For changepoint 2, there is no clearly defined cause. Changepoint 3 is attributed to the arrival of Lebanon multinational (peacekeeping) force (MNF) that triggered a rise in kidnappings in Lebanon and throughout the Middle East. The eventual fall in these kidnappings by 1988 results in changepoint 4. At times, certain countries or regions were plagued with a spate of kidnappings — see changepoints 5 and 7. An important recent changepoint followed the Abu Ghraib revelations at the start of April 2004 that resulted in myriad kidnappings of foreign contractors and aid workers in Iraq (Enders & Sandler, 2006, Table 7.3, 174). Thus, changepoints 1, 3, and 9 followed from policy decisions with unintended awful consequences. Many of the breaks in Table 4 have not been identified previously, thus underscoring the importance of our procedure. Notably, 9/11 is not a changepoint.

Figure 5 shows the SKYJACK series results, where there are eight breaks in the series, indicated by the vertical lines. Once again, the solid line is the cumulative number of SKYJACK events and the dashed line is the estimated arrival rate of new events. The information on the changepoints from Figure 5 is summarized in Table 5, along with confidence intervals, direction of change, and precipitating events. Two important contrasts between the KIDNAP and SKYJACK series are worth highlighting: SKYJACK

⁶ The prior sets $k_{max} = 50$, $\alpha = 1$, $\beta = L/n$, which is the elapsed days from the first event divided by the total number of events, or a very low prior step height for changes, $\lambda = 2$ or a prior of two changepoints. This prior is consistent with the Bai-Perron breakpoint analysis results of Enders & Sandler (2005). Using a larger prior number of changepoints merely generates clusters of changepoints around those reported here.

⁷ The posterior sample of the parameters passes standard diagnostic tests for convergence (Gelman and Rubin potential scale reduction factors computed using multiple chains are all one, traceplots show good mixing and convergence, and the acceptance rates of the acceptance rates for the Hasting steps for the number of changepoint are between 35-55%.)

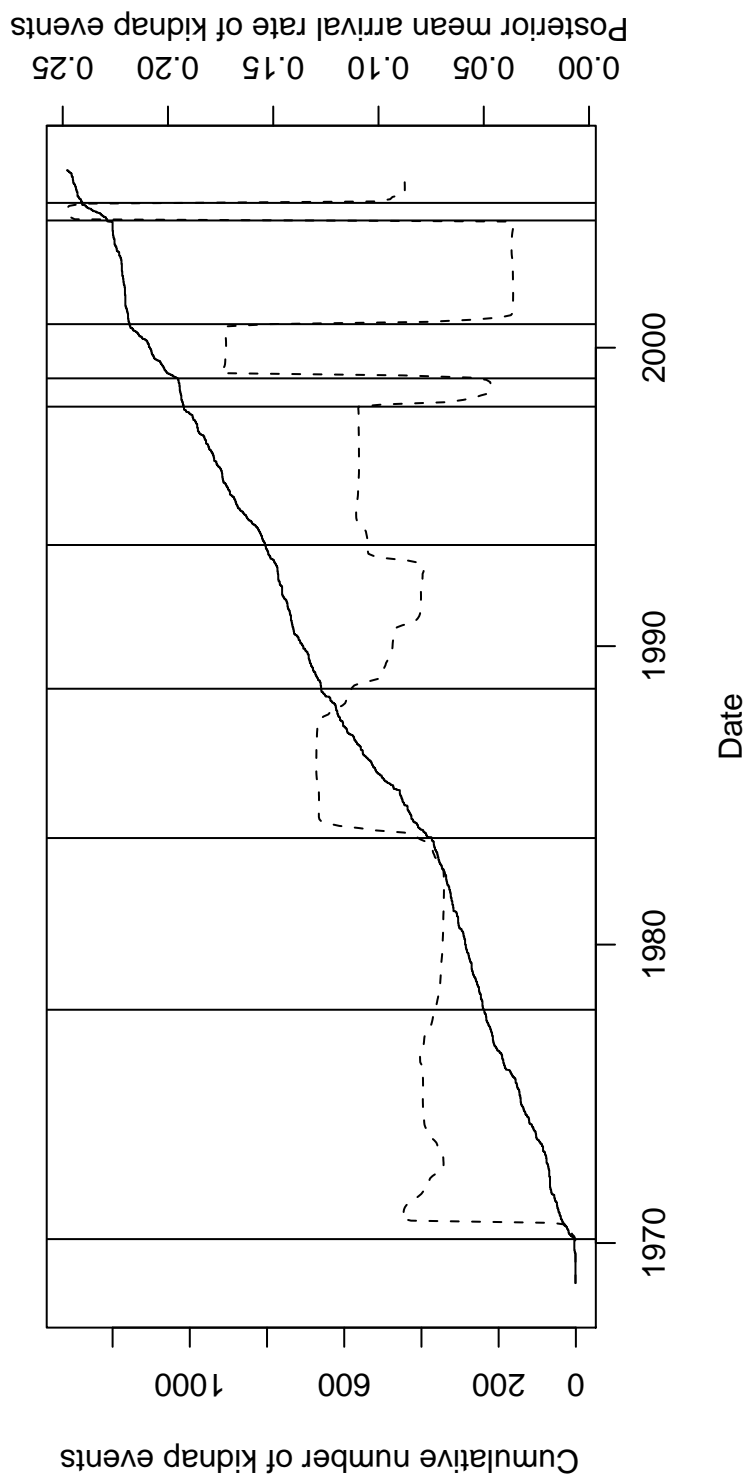


Fig. 4. Cumulative number of KIDNAP events and the posterior arrival rate of kidnap events, 1968–2005.

Table 4. KIDNAP event changepoint dates and their 68% credible intervals, 1968-2005.

Changepoint	Median Date	68% credible set	Direction	Event
1	1970-02-17	(1970-01-28, 1970-02-25)	+	Rise of transnational terrorism
2	1977-10-25	(1971-08-19, 1983-06-21)	-	Small decline in kidnappings
3	1983-07-27	(1983-04-22, 1988-03-17)	+	Lebanon MNF, rise in Middle East kidnappings
4	1988-07-27	(1987-09-16, 1991-10-26)	-	Downturn in Middle East kidnappings
5	1993-05-22	(1992-09-01, 1994-01-17)	+	Algerian/Turkish kidnappings
6	1998-01-09	(1997-12-20, 1998-04-02)	-	Drop in transnational terrorism
7	1998-12-21	(1998-12-01, 1999-01-05)	+	African / Latin American kidnappings
8	2000-10-14	(2000-09-19, 2000-11-24)	-	Pre 9/11 drop
9	2004-04-05	(2004-03-30, 2004-04-07)	+	Abu Ghraib revelations
10	2004-11-06	(2004-11-02, 2004-11-15)	-	Reduction in Iraqi kidnappings

has fewer changepoints, and the changepoints differ between the two series. This last observation means that past studies — e.g., Enders & Sandler (2005) — that aggregate all hostage events miss important breaks in the series. In Table 5, changepoint 1 corresponds to a number of well-publicized PFLP skyjackings that demonstrated to terrorists worldwide that well-executed seizures with lives hanging in the balance not only capture media attention, but may also yield concessions. The introduction of metal detectors at the start of 1973 led to a fall in skyjackings as the U.S. lead on January 3, 1973 was gradually followed by other countries over the next six months. Changepoint 3 is attributed to Cuban exiles commandeering U.S. planes to Cuba, a practice that finally ended (changepoint 4) once Castro dished out 40-year sentences to hijackers upon arrival and passengers started to take matters into their own hands. Changepoint 5 is associated with a large number of skyjackings in the Soviet Union prior to its collapse in 1991. The reduction in state-sponsored terrorism after the Cold War is matched to changepoint 6, while the decline of all forms of terrorism in 1996 may explain changepoint 7. Finally, increased airport security is tied to changepoint 8.

Figure 6 shows the cumulative number of OTHER hostage events and their arrival rate. The four changepoints are marked with vertical lines that match the entries in Table 6. Note that these breaks are much more spaced out — there are roughly six to eight years between each break. Large shifts in the arrival rate occur from late 1975 through 1985. Barricade missions and nonaerial hijackings lost their popularity in the late 1980s, thus explaining the paucity of changepoints after 1985. In Table 6, the four changepoints are matched to precipitating causes. Efforts to secure airports and other actions to protect business people from kidnappings resulted in a substitution into other kinds of hostage events — changepoint 2. As embassies were fortified in 1985, there was a drop in barricade missions (Enders & Sandler, 1993, 2006). Finally, the post-Cold War reduction in state-sponsored terrorism is tied to changepoint 4.

It is noteworthy that as hostage taking missions become more difficult (e.g., skyjackings are more difficult than kidnappings) that the number of changepoints fall from Table 4 to Table 6. Quite simply, innovations and shocks are more difficult to achieve for more difficult missions. The arrival rate changes are plotted together in Figure 7. The KIDNAP and SKYJACK events are negatively correlated ($r = -0.12$), which is indicative of substitutes. Thus, as metal detectors cut down on skyjackings, terrorists substituted into kidnappings, not protected by these detectors. The arrival rates of KIDNAP and OTHER hostage events are uncorrelated ($r = -0.01$). In contrast, these arrival rates are positively correlated ($r = 0.15$) for SKYJACK and OTHER hostage events, where the location is known to authorities. This positive correlation is indicative of complements.

The identification of substitute and complement modes of hostage taking is essential to informed and effective policymaking. Policymakers must anticipate that actions to reduce one attack mode will be somewhat offset by greater reliance by terrorists on a substitute mode. Thus, the authorities must also protect against this anticipated substitution with foresight. In the case of complementary modes, a single policy intervention is apt to reduce both forms of hostage taking. If hostage models are uncorrelated, then a policy intervention for one mode is unlikely to have repercussions on the other attack mode.

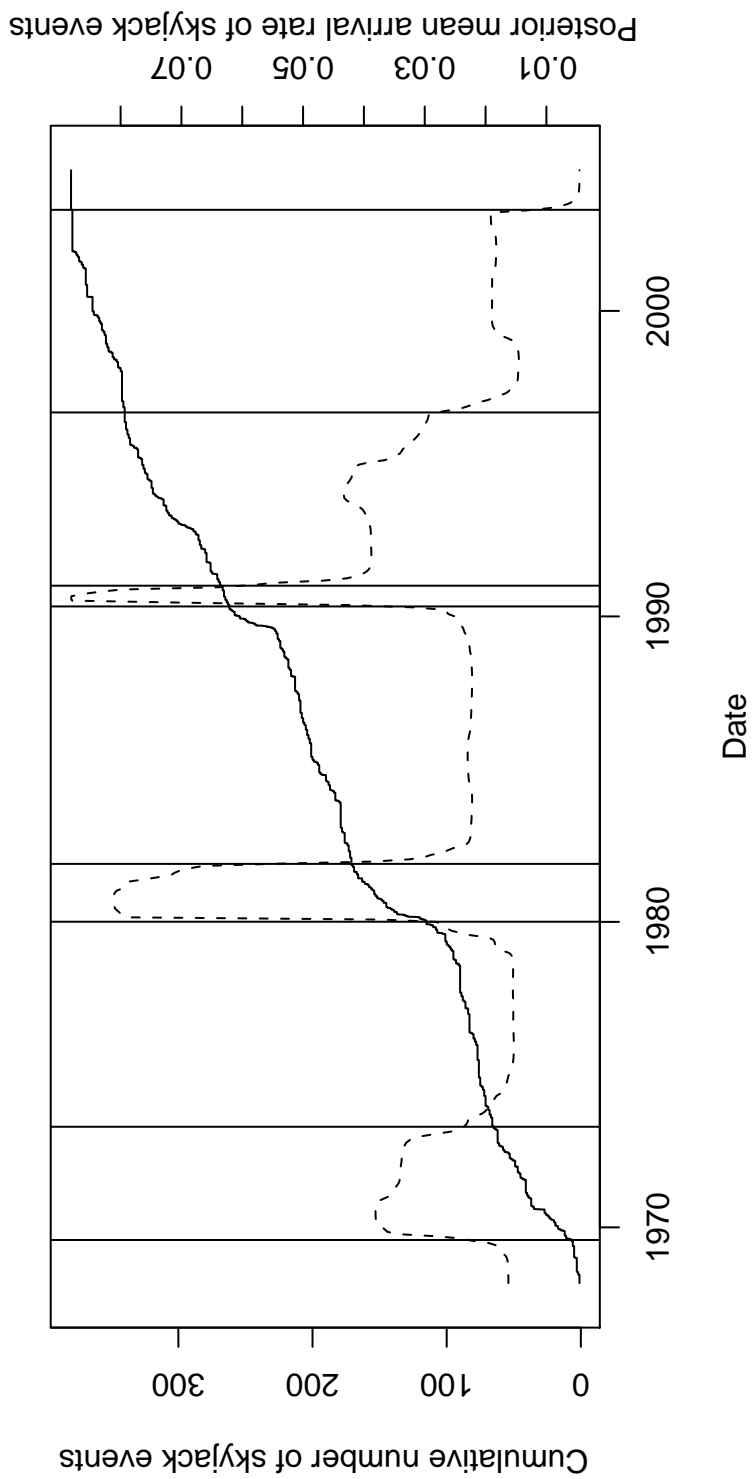


Fig. 5. Cumulative number of SKYJACK events and the posterior arrival rate of skyjack events, 1968–2005.

Table 5. SKYJACK event changepoint dates and their 68% credible intervals, 1968-2005.

Changepoint	Median Date	68% credible set	Direction	Event
1	1969-08-02	(1969-05-09, 1973-03-12)	+	PFLP skyjackings demonstration effect
2	1973-04-17	(1972-10-18, 1979-11-10)	-	Metal detectors
3	1980-01-02	(1979-06-04, 1981-10-12)	+	Cuban skyjackings
4	1981-11-24	(1981-06-09, 1987-08-03)	-	Castro 40-yr sentences
5	1990-04-29	(1986-01-15, 1990-06-15)	+	Soviet skyjackings
6	1991-01-02	(1990-05-21, 1995-04-10)	-	End of Cold War
7	1996-09-03	(1994-12-15, 1998-08-08)	-	Low terrorism year
8	2003-04-23	(1999-07-10, 2003-06-27)	-	Increased airport security

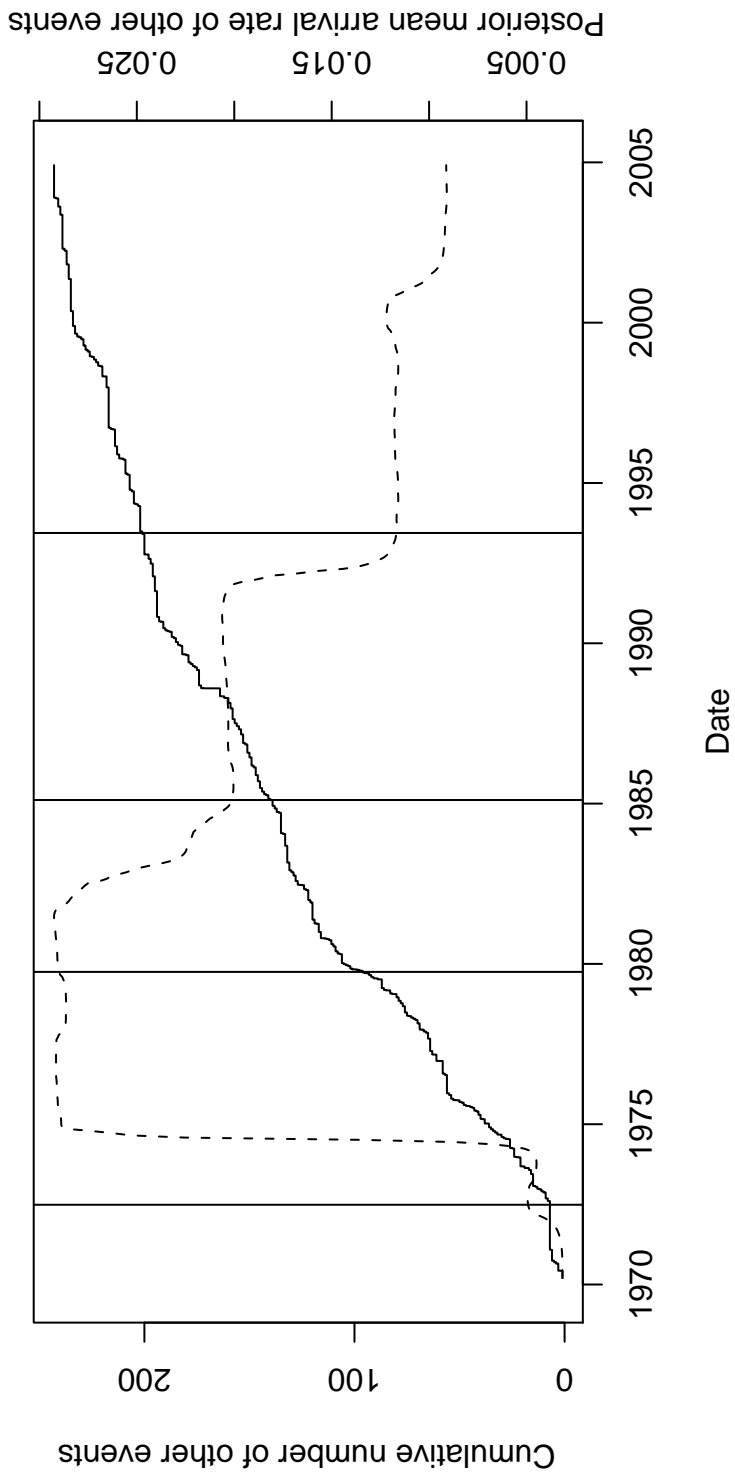


Fig. 6. Cumulative number of OTHER hostage events and the posterior arrival rate of nonkidnap events, 1968–2005.

Table 6. OTHER event changepoint dates and their 68% credible intervals.

Changepoint	Median Date	68% Credible Set	Direction	Event
1	1972-06-26	(1969-11-17, 1972-09-04)	+	Post-Israeli occupation
2	1979-10-01	(1972-08-14, 1981-10-31)	+	Substitution into other hostage events
3	1985-02-10	(1981-02-28, 1991-09-10)	-	Embassy fortification
4	1993-06-10	(1991-05-26, 2001-02-11)	-	Post-Cold War reduction

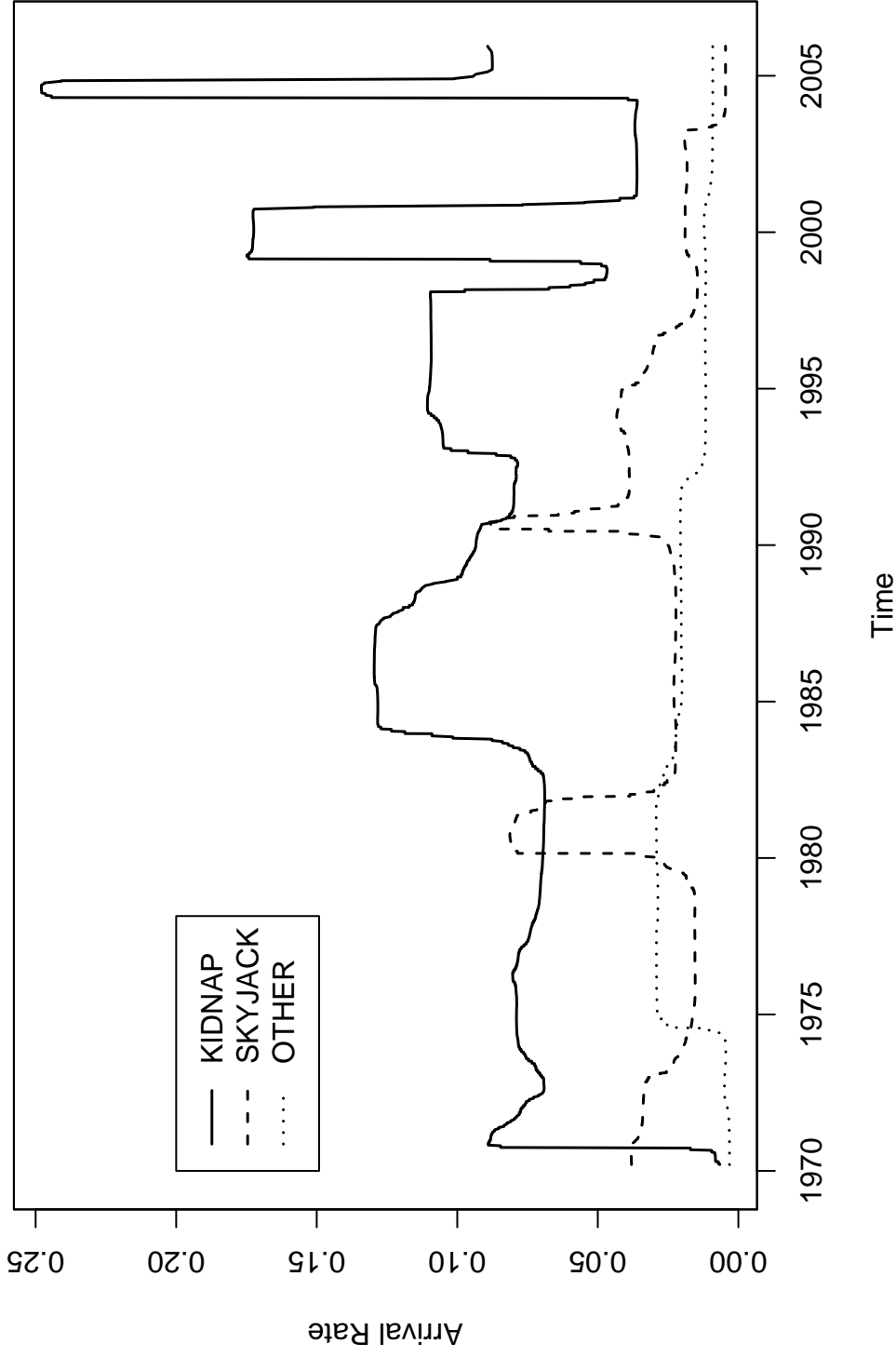


Fig. 7. Estimated arrival rates for each type of hostage event, based on the RJ-MCMC changepoint model, 1968-2005

5. Concluding remarks

This paper investigates the dynamic properties of three hostage taking series — kidnappings, skyjackings, and other hostage events. Based on the Poisson autoregressive model, we identify the lag structure of these three series for monthly and quarterly data, as well as the impacts of three covariates (i.e., successful negotiations, violent ends, and deaths). These impacts are expressed in terms of an impact and a long run multiplier. In the latter half of the paper, we apply a changepoint model estimated using reversible jump Markov chain Monte Carlo methods to identify the changepoints for the three series and to relate these breaks to the precipitating event.

This study shows that the level of aggregation — monthly or quarterly — makes a difference in the inferences about the dynamics of the series and the impacts of covariates. Moreover, we show that the covariates have different impacts on various hostage series. This indicates that policy recommendations for, say, kidnappings do not necessarily apply to skyjackings or other hostage events. For example, past concessions granted have the strongest impact on inducing future kidnapping events. For quarterly data, each successful negotiation results on average in 2.62 additional abductions over time. In fact, violent ends encourage further kidnappings and other hostage events, a disturbing and unexpected finding.

When changepoints are investigated, we find that each type of hostage event has different changepoints. The more risky the event, the fewer are the number of changepoints. These differences again underscore that policy recommendations must distinguish among the various types of hostage incidents. Another disturbing finding is that some policies — e.g., Lebanon MNF and Abu Ghraib abuses — have unintended negative consequences that generate a wave of kidnappings. Thus, changepoints may result from policies, political events, or terrorism hotspots. Past studies that only used counterterrorism policies to identify changepoints will miss many such points.

Kidnappings and skyjackings estimated arrival rates are negatively correlated so that policies that discourage skyjackings — e.g., airport metal detectors — may encourage kidnappings. This negative correlation, thus, alerts policymakers to account for such potential substitutions, which may call for multiple policy interventions to head off policy-induced transference of attacks. Since skyjackings and other hostage events estimated arrival rates are positively correlated, a single policy intervention may have a double dividend by curbing more than one terrorist tactic. When making allocation decision among alternative counterterrorism actions, policymakers need to account for such negative and positive correlations.

Our methods can be fruitfully applied to other terrorist tactics for policy and forecasting purposes.

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