Fair & Balanced or Fit to Print?
The Effects of Media Sources on Statistical Inferences

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Abstract

This paper examines the effects of source bias on statistical inferences drawn from event data analyses. Most event data projects use a single source to code events. For example most of the early Kansas Event Data System (KEDS) datasets code only Reuters news reports and code Agence France Presse (AFP) reports. One of the goals of Project Civil Strife (PCS) –a new domestic-based event data project– is to code event data from several news sources to garner the most extensive coverage of events and control for bias often found in a single source. Herein, we examine the effects that source bias has on the inferences we draw from statistical time-series models. In this study, we concentrate on Indonesia and Cambodia from 1980-2004 using automated content analyzed datasets collected from multiple sources (i.e. Associated Press, British Broadcasting Corporation, Japan Economic Newswire, United Press International, and Xinhua). The analyses show that we draw different inferences across sources, especially when we disaggregate domestic political groups. We then combine our sources together and eliminate duplicate events to create a multi-source dataset and compare the results to the single-source models. We conclude that there are important differences in the inferences drawn dependent upon source use. We conclude that researchers should (1) check their results across multiple sources and/or (2) analyze multi-source data to test their hypotheses.

Introduction

Political scientists in many of the major subfields often analyze data compiled from media reports to test hypotheses implied by different political theories. For example, in American Politics, Caldeira (1987), Neuman (1990), Page, Shapiro, and Dempsey (1987) and others investigate the relationship between public opinion and news content. In comparative politics, Davenport (1995), Moore (2000), Francisco (1993) and others analyze media generated data to explain intranational conflict processes. In international relations, Goldstein (1990 with Freeman; 1991 with Freeman; 1997 with Pevehouse), Schrodt (2000; 1998 with Gerner), Moore (1995) and others examine media generated foreign policy behavioral measures to understand conflict-cooperation relationships among states. Finally, in public policy studies, Wood and Anderson (1993) investigate the public awareness of a policy issue using data gathered from media reports. All of these studies draw their inferences from media generated data. Furthermore, many of these studies analyze data generated from a single media source.

This study examines source bias and its potential effects on the scientific inferences we draw from our statistical models. While our study should prove useful for all fields in political science, in particular, we wish to examine how media generated data affect inferences drawn from dynamic intranational conflict-cooperation time-series models. To do so, we analyze the potential bias of various sources on their coverage of Indonesian and Cambodian domestic political conflict and cooperation events from 1980-2004. We contend that single source generated event data only provide one account of the true data and that other sources may provide alternative accounts of domestic conflict-cooperation processes over the same time period.

Event data are the day to day coding of political events as reported in the open press. Generally, these data record the date and who did what to whom. While the original data code individual actions, these events are often scaled on a hostility-cooperation continuum. Such scaled data are often used in studies of international (e.g. Goldstein and Freeman 1991) and intranational (e.g., Francisco 1993; Moore 1998) conflictual and cooperative interactions. Additionally, students of American and comparative politics use media-generated datasets to track information such as the number of strikes, protests, and riots in a particular country or region of a country (e.g., Franzozi 1987).

Over the last decade, several studies examine the validity and reliability of media generated event data and as a consequence develop a small literature on this topic. These studies answer different questions and/or analyze some aspect of the validity and reliability of events data. For example, there are studies which assess the coding (machine v. human) (Schrodt and Gerner 1994), scaling (Goldstein 1992; Shellman 2004b), and aggregation (Freeman 1989; Shellman 2004b) processes, as well as the bias associated with particular sources (Woolley 2000; Francisco 2006; Davenport and Ball 2002; Gerner and Schrodt 1998).

In this paper, we contribute to that literature and assess to what extent the media source influences causal inferences drawn from statistical models. To answer this question, we first analyze event datasets generated by single sources and assess the degree to which our inferences are influenced by our different source generated datasets. Next, we combine the single source datasets together and assess the inferences we draw from the multi-source event datasets. In short, we find that our different media-based datasets produce different results.

While our study contributes to the literature on media bias and event data, the study also serves a corollary function. It performs an assessment of a few of the newly collected Project Civil Strife (PCS) datasets.[1] Project Civil Strife is an event data project designed to quantify the behavior of multiple groups competing within a polity, including but not restricted to governments and rebel groups. A machine procedure codes the actors, targets, events, and dates of events reported in multiple electronic media reports. We chose the recently collected Cambodia and Indonesia datasets to assess whether or not the source of the coded media reports affects our inferences drawn from statistical models.

Our study proceeds as follows. First we briefly review the literature on this topic and highlight the contribution of our paper. Second, we describe Project Civil Strife and our event data coded from multiple media sources. Third, we describe the models we employ to assess how inferences are affected by the source of the data. Fourth, we present descriptive and inferential statistics which reveal differences across our sources. Fifth, we conclude by recapping our findings and conclude our paper by making a few recommendations to researchers working with such data.

The Literature & Contribution

Content analysis of news reports allows researchers to extract information on political events reported in electronic sources like Reuters, BBC, Agence France Presse, and The New York Times. It should be no surprise that each of these sources provides a unique coverage of events. Potentially, language, style, depth, breadth, and characterization of coverage by a source can influence the way an event is coded or even if it is coded at all. Woolley (2000) argues that the most common disparities amongst sources are regional biases, disproportionate coverage of urban areas, and a greater tendency to report events with large numbers of people. He shows that significant differences in media-reporting

[1] See the PCS Codebook for additional information on the datasets (Shellman, Stewart, and Reeves 2006).

exist even among large-scale events such as coups and assassinations (Woolley 2000). Given these differences, the choice of source for event data can have a major impact on the results observed.

Davenport and Ball (2002) also investigate the implications of source selection by comparing the coverage of Guatemalan state terror across newspapers, human rights documents, and eyewitness accounts. While their results suggest that each source covers different characteristics of state repression, they find that newspapers yield the best coverage and the most information. They further confirm that newspapers tend to record information for urban as opposed to rural areas and that the presence of widespread violence increases the likelihood that any individual act of violence will be covered. The authors also found that newspapers in unrestrictive regimes are more likely to communicate the facts without being censored.

Davenport and Stam (2006) undertake a similar study of differences in accounts of the Rwandan genocide. They find that newspapers differ from NGOs and government sources in their range of coverage, as well as in their focus on large-scale and controversial events. They illustrate several concerns about media sources, such as the occurrence of media fatigue and the news agencies' reliance on the government for information. This reliance on official sources, which are prone to supplying biased data, is an especially large problem in areas plagued by violence, where journalists are unable to travel freely to collect information. Davenport and Stam emphasize that different sources have differing perspectives and advocate careful analysis of the structure of the situation in which these events are reported.

However, these two articles do not investigate how newspapers differ with respect to coverage. Instead they stake their claims on an event dataset generated from several newspapers and/or NGO and government sources. Schrodt's and Gerner (1994) analyze the differences in reporting between regional chronologies and an international news agency (Reuters), and a later study by Schrodt, Simpson, and Gerner (2001) compares Reuters against Agence France Presse. These studies examine the correlation in number and type of events reported for particular conflict dyads, and they conclude that different news sources are complementary. Schrodt, Simpson, and Gerner (2001, 36) write:

> Reuters and AFP are comparable in terms of the general patterns of events they report. They are not, however, identical sources of information…Reuters provides denser coverage in the Balkans… What seems to be important here is not only that AFP differs in style from Reuters, but that there are regional differences in AFP as well. This suggests that sometimes Reuters is in the right place at the right time, and sometimes AFP.

In the above cases, the authors' primary concern is explaining coverage. By contrast, our primary concern is whether or not the data across different datasets (collected from different media sources) yield different inferences when the different datasets are analyzed using the same statistical method. In comparative case study research, analyzing conflict data from two separate cases both collected by a single source could result in biased inferences if such regional differences of coverage as found by Schrodt, Simpson, and Gerner exist. Moreover, if two sources differ with respect to coverage, we ought to question the validity of inferences we draw from event data compiled from a single source.

Other research in this area suggests that newspapers may not provide a representative sample of the true universe of events. Woolley (2000) argues that we need to crosscheck our datasets collected from newspapers with a standard "benchmark." Francisco (2006) takes this charge seriously and compares intranational event data compiled from news sources to detailed chronologies of events for particular countries. He concludes that a benchmark source may not exist in the field of protest and repression, as "putative benchmarks perform poorly in density tests against [event data collected from] multiple sources" (Francisco 2006, 18). Francisco (2006, 18) argues that "multiple sources provide the best antidote to source bias." His study illustrates that wire services are superior to newspapers, as the former face fewer space and advertising-related limitations on the amount of information published.

The findings from these studies and others suggest that source bias deserves more attention. Our paper contributes to this literature by analyzing single and multiple source event datasets and analyzing whether single source bias influences the scientific inferences we draw from statistical models. Furthermore, we expand on earlier tests of media bias by comparing a wider range of news agencies, and we go beyond correlation in number and type of events to examine statistical differences in actors' behavior over time. In the next section we describe the Project Civil Strife data we choose to analyze in this study.

Project Civil Strife

The goal of Project Civil Strife (PCS) is to contribute several systematic empirical time series case studies of civil conflict dynamics in Burma, Cambodia, Indonesia, Laos, Malaysia, the Philippines, Thailand, and Vietnam from the 1980's through the present. The project contributes three separate, but related, datasets. PCSCOMMON uses automated coding of English-language news reports to generate multi-actor political event data focusing on Southeast Asia. PCSTERROR captures domestic terrorism events in Southeast Asia. PCSGROUP gathers information on relative power, structure, ideology and other general characteristics of groups represented in the COMMON and TERROR databases. These data are used in statistical models to predict and explain political change.

The focus of this study is on the PCSCOMMON data. The project focuses on conflict and cooperation taking place among domestic and government actors within countries. Specifically, PCSCOMMON aims to code levels of conflict and cooperation exchanged between myriad political, rebel, ethnic, religious, social, and economic actors.

PCSCOMMON uses a modified version of Text Analysis By Augmented Replacement Instructions (TABARI), developed by Phil Schrodt, to generate domestic political event data.[2] TABARI uses a "sparse- parsing" technique to extract the subject, verb, and object from a sentence and performs pattern matching using actor and verb dictionaries.[3] In short, TABARI matches words from an electronic text file (news story) to words contained in the actor and verb dictionaries and assigns a corresponding code to each actor and verb. It also records the date. Machine coded data are only as good as the dictionaries, and thus each of the actor dictionaries is customized for each case. While most event data sets (internal and intranational) code events from a single news source,[4] we currently code events from multiple electronic news sources available through Lexis-Nexis. The process begins when a student familiar with the history of their case combs through historical references, group datasets and news reports to develop the country-specific actor dictionary and determine the principle sources to be coded. Following the initial stages of development, we test the dictionary by coding eve nts one at a time in TABARI. We perform these tests in order to identify systemic errors in the coding, which we fix by adding additional verbs or actors to our dictionaries. We then rerun TABARI in the "automated" mode in order to obtain the final results.

The events are coded according to a verb dictionary. Our verb dictionary is a modified KEDS verb dictionary. Verbs and verb phrases are assigned a category based on the WEIS coding scheme.[5] KEDS has introduced new codes in addition to those used by

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[2] See http://raven.cc.ukans.edu/~keds/index.html for information on the KEDS and TABARI projects.
[3] TABARI recognizes pronouns and dereferences them. It also recognizes conjunctions and converts passive voice to active voice (Schrodt 1998).
[4] For example, early KEDS data and IPI data come from *Reuters*, while later KEDS data come from *Agence France Presse*. WEIS data come from *The New York Times Index*.
[5] See "World Event/Interaction Survey (WEIS) Project, 1966-1978," ICPSR Study No. 5211.

McClelland and the WEIS project; most of which are borrowed from the PANDA project.[6] While many of the KEDS verbs are relevant to intranational conflict, the file is missing verbs that appear in stories on civil conflict. We build on those codes when necessary using verb lists developed by each case builder looking through news reports. We then use the Goldstein (1992) scale to weight each category on a cooperation-hostility continuum.

Research Design

Data

In this study, we analyze several datasets compiled for Cambodia and Indonesia. The actor dictionaries for each case are very extensive. They code specific individuals as well as groups. For example, in Cambodia, this includes actors from President Norodom Sihanouk of the Resistance Coalition Government and FUNCINPEC all the way down to Ti Yav, the Vice Minister of Planning. In addition to thousands of unique individuals specified, the Cambodia actor dictionary captures individual political, social, religious and dissident groups and leaders. All told the actor dictionary for Cambodia includes 8393 terms representing some 1400 different codes. The net result is a data set that is capable of functioning on a highly disaggregated level.

First, we create five different single source datasets for both Indonesia and Cambodia. Specifically, we generate datasets from press reports distributed by Associated Press (AP), British Broadcast Corporation (BBC), Japan Economic Newswire (JENW), United Press International (UPI), and Xinhua available in the Lexis-Nexis database. BBC, UPI, and Xinhua cover the period 1980-2004. AP covers the period 1985-2000 and JENW covers the period 1992-2004.[7] Schrodt et al. (2001) suggests the possibility of creating

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[6] See http://www-vdc.fas.harvard.edu/cfia//pnscs/panda.htm for information on the PANDA project.
[7] Both sources' coverage varied in Lexis-Nexis.

multiple source chronologies from TABARI generated data and in the end concludes it is feasible and should be done. Heeding this advice along with that of Francisco (2006), we create one dataset using all five sources and another dataset using the BBC, UPI, and Xinhua data, given that they cover the same temporal domains. To do so, we wrote a software program that would combine all the datasets together and then remove the duplicate events coded each day by different sources. For example, if the date, actor, target, and verb phrase matched across sources, we removed the duplicate event(s). If it does not, we keep it in our multi-source datasets.

[Insert Tables 1 & 2 about here]

Table 1 (A and B) reports both the total number of hostile events per the Goldstein (1992) scale and all events coded from each source for Indonesia and Cambodia, respectively. Important differences exist in the style and content of the media sources used. In the case of Cambodia, BBC and Xinhua had by far the most extensive coverage, which was in large part due to these services carrying press releases and propaganda statements from the government and dissident factions. Xinhua, as the state news agency of the People's Republic of China, reported most often on the resistance groups, whom the Chinese actively supported. The resistance groups' propaganda tended to report large numbers of small-scale military actions, which were duly picked up by Xinhua and to a lesser extent by BBC. The other sources - AP, UPI, and JENW – did not carry government or dissident propaganda. All of the sources are a wire service and provide unfiltered news reports for distribution electronically amongst newspapers. They each had varying degrees of coverage across the cases. BBC, UPI and Xinhua had the full breadth of coverage from 1980-2004 with BBC and Xinhua providing the greatest depth. AP and JENW both had limited breadth of coverage available on Lexis-Nexis. They also possessed varying degrees of depth across cases, somewhere between the level of coverage offered by BBC and the level of coverage offered by UPI.

Table 1 shows that BBC codes the most events in both Indonesia and Cambodia, while UPI and JENW code the least amount of events in Indonesia and Cambodia, respectively. BBC codes the most cooperative events across the two countries of any source, while AP and UPI code the most hostile events across both cases. Not surprisingly, combining the relevant datasets yields percentages of coded hostile events very close to averaging the relevant percentages across the sources. For example, BBC, UPI, and Xinhua combined in Indonesia code 41% of all events as hostile events. This is fairly close to taking the average of the three sources (43%). The same holds true for Cambodia. The three combined data sources code 48% of all events as hostile, and the average of the three percentages is 48.6%. We observe the same relationship across all five datasets for both countries. The combined percentages closely reflect the average of the percentages across all five sources. We find it interesting that there is not more bias in each source to report more violent and hostile events than cooperative and accommodative events.

One can surmise that the cooperative events that took place in these countries were significant enough to generate an equal degree of attention from media sources, compared to hostile actions that are sometimes considered more "news-worthy." Government and resistance propaganda would have an equal or greater incentive to publicize their peacemaking exploits, and thus BBC and Xinhua would likely carry large numbers of cooperative actions. We may be observing media fatigue in action, with hostile events being so commonplace in an insurgency-plagued country that news agencies are less likely to report them in comparison to relatively new and unique efforts at reconciliation.

Event Scaling & Aggregation

To use statistical techniques, such as ordinary least squares (OLS) regression, the WEIS/KEDS event codes must be transformed into an interval-like measure of conflict-cooperation. To do so, we use the interval weights reported in Goldstein (1992), which surveys expert conflict scholars to produce an interval-like scale of conflict-cooperation for the WEIS event data, where positive numbers indicate cooperation (>0 to +10) and negative numbers indicate hostility or conflict (<0 to -10). We also use the additional KEDS weights when necessary. Now that we have interval-like conflict-cooperation data, we must convert the events to a time-series by temporally aggregating the data.

Shellman (2004a; 2004b) finds that aggregation decisions affect coefficient estimates, block exogeneity tests, and standard errors. Shellman's results are consistent with Goldstein and Pevehouse and Franzosi in that smaller temporally aggregated units tend to reveal stronger statistically significant partial-correlation coefficients than larger units. Goldstein and Pevehouse report that (1997, 207) "High levels of aggregation (such as quarterly or annual data) tend to swallow up important interaction effects" and Franzosi (1995, 72) shows that "the more aggregated the series, the less likely it is to detect the effects of strikes on production." The results of these studies support Wood's (1988) contention that smaller temporal units allow one to better sense the causal mechanisms at work.

Given these findings in the literature, we choose to aggregate our data by the week. Daily aggregated data prove to be too small of a unit; there is almost certainly a lag effect at the daily level between government and rebel interactions and it is difficult to model such a lag structure. Following Goldstein and Pevehouse (1997), we aggregate our event data by the week, which allows us to maintain a relatively small temporal unit and not be bogged down with too many lagged variables (many of which would contain zero values at the daily level).

There is less of a literature on how we should aggregate domestic conflict data across actors. Almost all of the studies in this literature develop two-actor theoretical and empirical models. That is, they aggregate all the dissident actors' behavior together and all of the government's behavior together and generate two directed dyad variables. Following the previous studies' lead, we aggregate all dissident behavior directed towards the government together and all government behavior directed towards the dissidents together to create two directed dyad variables.[8]

In addition to analyzing the two directed-dyadic aggregate variables outlined above, we disaggregate the rebel groups in Cambodia into the four major groups represented in the conflict: Democratic Kampuchea (DK), the National United Front for an Independent, Neutral, Peaceful, and Cooperative Cambodia (FUNCINPEC), the Khmer People's National Liberation Front (KPLNF), and the resistance coalition (formed among the three previous groups). Then we generate 8 directed dyad variables, one for each rebel group's behavior directed towards the government and one for the government's behavior directed towards each rebel group.[9] Below, we elaborate on the statistical models we use to compare inferences across our different datasets.

[8] In Cambodia, the People's Republic of Kampuchea is backed by Vietnam, who controls many of Cambodia's state functions through 1989. Thus, we include Vietnam actors as part of the government up until Vietnam leaves the country in 1989. We also account for leaders and groups changing from rebels to governments and vice versa over time via in our coding scheme.

[9] We also aggregate the Cambodian data into two directed dyad variables by aggregating all four groups' behavior towards the government together and the government's behavior towards the four groups together. However, we do not report those results in table and figure form given space constraints.

Methodology

Our goal is to determine whether or not source bias affects the inferences we draw from statistical tests. To do this, we choose two standard models from the literature, a vector autoregressive (VAR) model and a vector error correction (VEC) model. While VAR models are more frequently used in the intranational conflict literature, both VAR and VEC models appear consistently in the international conflict literature. Briefly we sketch how each model can test a few hypotheses from the literature. This also allows us to organize our discussion of results around different hypotheses and illustrate how results from different data affect our inferences.

Most of the literature agrees that repression affects dissent and dissent affects repression; they just disagree in the ways they affect each other. These different studies also invoke different theoretical explanations that give rise to different hypotheses. Most of these theoretically informed studies fall into two camps: retrospective and prospective. The retrospective studies more or less argue that governments and dissidents react and respond to one another's behavior, while the prospective studies contend that governments and dissidents generate rational expectations about the opposing actor's behavior and act based on their expectations.

A typical action-reaction model or retrospective model is often captured by a standard system of parameterized VAR equations:

$$GOV_t = a_1 + ß_{11}\, GOV_{t-1} + ß_{12}\, REB_{t-1} + e \qquad (1)$$
$$REB_t = a_2 + ß_{21}\, REB_{t-1} + ß_{22}\, GOV_{t-1} + e \qquad (2)$$

where GOV_t and REB_t represent government and rebel actions at time t, respectively. The model can aid in testing multiple hypotheses from the literature.[10] Positive and

[10] Some argue that (H1) hostility discourages hostility and encourages cooperation (e.g., Snyder and Tilly 1972; Tilly 1978, Moore 2000; 1998; Francisco 1995; 1996; Lichbach 1987) while others posit that (H2) hostility encourages hostility (Gurr 1970; Hibbs 1973; Francisco 1995; 1996). Additional

statistically significant coefficients on the opposing actor would support the reciprocity hypothesis that actors return roughly equivalent values of hostility and cooperation contingent on the prior action of the other actor (Keohane 1986, 8). Negative coefficients would indicate backlash or inverse behavior, such that one actor returns cooperation for the other actor's hostility and hostility for cooperation. Likewise, if the coefficients on their own past behavior are positive and significant, the model would show that the actors continue to do what they themselves have been doing – what Goldstein and Freeman (1991, 23) refer to as "policy inertia." Given the problem of collinearity among the lagged independent variables, we perform Granger causality tests (i.e., joint-F tests) on the set of coefficients corresponding to each actor's lagged behavior. The tests assess whether one series Granger-causes the other. If we find that both series Granger-cause each other, we infer that actors "react" to e ach other's behavior.

Of course these action-reaction models are widely criticized. McGinnis & Williams (1989; 2001; Williams and McGinnis 1988) essentially argue that policy-makers anticipate what their rival is going to do next and act accordingly. Thus, the past behavior of the other actor should not significantly affect one's current behavior. Instead, actors should seek to limit the other actor's strategic gains. The argument, briefly sketched here, expects actors to choose a hostility level that would roughly match the hostility level anticipated by their opponent. When their expectations are violated by reality, we expect the actors to react to their errors and develop new expectations about their rivals. Moore (1995) extends this argument to rebels and governments. One way to model a rational expectations approach is

scholars argue that (H3) cooperation encourages hostility (or decreases cooperation) (e.g., Rasler 1996), while still others claim that (4) cooperation encourages cooperation (e.g., Krain 2000; Carey 2004). Finally, a fifth hypothesis combines a couple hypotheses and contends that actors reciprocate one another's behavior. A s such, support for hypotheses 2 and 4 together would corroborate the reciprocity hypothesis.

to use a VEC model. Though most scholars incorrectly contend that error correction models can only be estimated using nonstationary, cointegrated series, Deboef and Keele (2005) argue that error correction models need not be tied to cointegrated series which independently are non-stationary or I(1). They argue that error correction models can be applied to two non-stationary series. Dickey-Fuller tests of our series indicate that all of our series are I(O) or stationary (they have a constant mean and variance). Using Deboef and Keele's (2005, 13) advice that error correction models are "perfectly suitable for stationary data," we estimate VEC models on our stationary series. Series are "cointegrated" if a linear combination of the series produces a stationary series.

We use the Johansen methodology to estimate our VEC models. The VEC regression model produces parameters for three equations: the cointegrating equation and the two vector error correction equations. To test our rational expectations hypotheses we specify a two equation VEC model composed of government behavior direct towards rebels (GOV) and rebel behavior directed towards the government (REB). Doing so allows us to investigate whether the two series share a long-run equilibrium relationship. A rational expectations hypothesis would suggest that both series share a common trend such that the two series form a stationary series in and of itself. Thus, we are interested in determining whether

$$GOV_t - d_1 \quad REB_t - a = ?_t \tag{3}$$

where $?_t$ is a 0 mean, normally distributed, stationary series. Let $d_1 = (1, - d_1, ?_t)$ be the cointegrating vector. The constant, 1, is associated with GOV_t and has a positive sign. If the directed dyadic behavior of governments and rebels is driven by an error correction process, then d_1, which represents REB_t in this representation, will be statistically significant and will have a negative sign.[11]

We then estimate the two vector error correction (VEC) equations below.

$$?GOV_t = a_1 + ß_1 d_1 + S ß_{11} ?GOV_{t-i} + ß_{12} S REB_{t-i} + e_{t1} \qquad (4)$$
$$?REB_t = a_1 + ß_2 d_1 + S ß_{21} ?GOV_{t-i} + ß_{22} S REB_{t-i} + e_{t2} \qquad (5)$$

where the *ß* ‘s are *i*-dimension vectors of parameters to be estimated, and *i* is the number of lags included in the VEC model. The EC parameters, $ß_1$ and $ß_2$, are the response rates and indicate how rapidly the series return to equilibrium. If the EC (response rate) parameters for $?GOV_t$ and $?REB_t$ yield opposite signs, the results suggest a rational expectations process is at work. Furthermore, the impulse response functions should show that the series respond to innovations in the other series.

We estimate these two systems of equations for each source across weekly datasets for Indonesia and Cambodia but only report the results for Indonesia. For Cambodia we report the results for the disaggregated multi dissident actor models. We expand the VAR two-actor directed dyadic models to multi-actor directed dyadic VAR models. That is, we regress past levels of all eight directed dyadic variables (i.e., DK towards government, FUNCINPEC towards government, KPLNF towards government, the resistance coalition towards the government, the government towards DK, the government towards FUNCINPEC, the government towards KPLNF, and the government towards the resistance coalition) on all current levels of the eight variables. Given the problems with multiple cointegrating vectors/equations and relationships among the eight variables, we run separate two-equation VEC models for each rebel-government directed-dyad (e.g., DK towards government and government towards DK) represented in Cambodia.

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[11] The sign will be negative because the constant, has a positive sign. If the series have a cointegrated relationship, they should have opposite signs.

To specify the appropriate lag lengths for the VAR systems, we estimated a series of VARs using a variety of lag lengths, but settled on four lags for both theoretical and empirical reasons. First, we use the week as our unit, so four lags representing one month of lags seems appropriate. We then compared several information criterion (e.g., the Schwartz Bayesian Information Criterion and the Akaike Information Criterion) from each model.[12] The criterion for a majority of the models selected four lags. We decided for comparison sake to run all of our models with the same number of lags and four made the most sense given the information criterion and face validity.

One problem we encounter when estimating a VAR system of equations are non-stationary series. Regressing one nonstationary series on another nonstationary series may produce a spurious relationship between the two variables and may result in falsely rejecting the null hypothesis. Therefore, one must check each time series that enters the VAR to see if it is stationary. We performed augmented Dickey-Fuller (ADF) tests on each temporal series in each VAR.[13] The results of the ADF tests show that each series is stationary.

To assess the direction of each relationship uncovered, we use vector moving average (VMA) methodology and plot the impulse response functions (IRFs). Just as an autoregression has a moving average representation, a VAR may be written as a VMA, in that the variables (GOV_t and REB_t) are expressed in terms of their current and past values of the two shocks to the system (i.e., e_{GOVt} and e_{REBt}).[14] Plotting the coefficients of the impulse response functions visually allows one to represent the behavior of the GOV_t and

[12] One may also choose to use the Akaike information criterion (AIC) to specify the appropriate lag length. I chose the SBC because the SBC will always select the more parsimonious model (see Enders 1995, 88).
[13] A summary of the results for the ADF tests is available from the author.
[14] See Enders (1995, 305) for complete specification.

REB_t series in response to various shocks. The simulations provide information on both the size and direction of the impact of each series, and thus provide information as to whether states' and dissidents' behavior is best characterized as policy inertia, reciprocity, or both. We also plot the IRFs for our VEC models.

Results

We organize our results around the two models and the rational expectations and action-reaction hypotheses. Given the large amount of output associated with 14 different datasets (seven for each country) and two different models, we do not report every coefficient and every impulse response function in this paper. However, we plan to provide all of our raw Stata output as well as display all of the impulse response functions for each model and dataset in figure form in an online appendix.[15] Herein, we choose to report the Granger causality tests for all VAR models in Indonesia and Cambodia but exclude the coefficient estimates. We also report the impulse response functions (IRFs) for all Indonesian VAR & VEC models but do not report them for the Cambodian eight-actor models given the total number of IRFs they produce per model per dataset. Finally, we report the coefficients for all of the VEC cointegrating equations and the VEC "response parameters," though we exclude the coefficients for the VEC lagged differenced variables.

VAR Granger Causality Results

We begin by analyzing the Granger causality tests calculated from our VAR models. A variable , X, is said to Granger-cause a variable Y if, given the past values of Y, past values of X are useful for predicting Y. A common method for evaluating whether or not X

[15] Upon publication of this study, we plan to post an Appendix associated with this paper at http://arches.uga.edu/~smshel/Research/Pubs_Papers.html.

Granger-causes *Y* is to fit a VAR and test whether the coefficients on past lagged values of *X* are jointly zero. We report the outcomes of those tests for our Indonesian government-rebel directed dyad VAR models in Table 2 and for our Cambodian specific dissident group-government directed dyad models in Table 3.

[Insert Table 2 about here]

Table 2 reveals that we would indeed draw different inferences from results produced from different datasets generated by different sources, but that inferences across sources are more congruent than we anticipated. To begin, we would infer using the UPI dataset that previous Indonesian government behavior does *not* Granger-cause Indonesian dissident behavior. However, all the other datasets show that previous Indonesian government behavior does Granger-cause Indonesian dissident behavior, though the JENW results are only significant at the .10 level. Moreover, we would infer from the JENW and Xinhua datasets that previous Indonesian dissident behavior Granger-causes Indonesian government behavior, while all the other datasets' results illustrate a statistically *in*significant finding. Note that the All and UBX (UPI, BBC, and Xinhua combined) datasets uphold the majority of the single-source data inferences. For example, we would infer from the results from four out of five single-source datasets as well as the All and UBX datasets that government behavior Granger-causes dissident behavior. Likewise, we would infer from the results from three out of five single-source datasets as well as the All and UBX datasets that dissident behavior does *not* Granger-cause government behavior. Overall, we were surprised that the inferences were so similar across sources. We address the topic of similarity among the multiple and single source datasets in our conclusion.

[Insert Table 3 about here]

Table 3 also reveals that we would draw different inferences from Cambodian results produced from different datasets generated by different sources. In fact, the effects from sources become more apparent across the multi-actor models than in the two-actor models. Table 3 is broken up into seven sub-tables, each corresponding to a particular source. Given space constraints, we concentrate on analyzing the Granger-causality tests for each dissident group and the government and spend little time analyzing how the relationships between other groups and the government affect a specific group's interactions with the government. For ease of reference, we have drawn boxes around the test statistics we discuss below.

We begin by analyzing the relationships between DK and the Cambodian government. Across the sub-tables, we would infer from the AP and BBC results that the Cambodian government does *not* Granger-cause the DK. However, all other datasets do show that the Cambodian government does Granger-cause the DK. Similarly, we would infer from the BBC and JENW that the DK does not Granger-cause the government, while the other source's results would corroborate the action-reaction hypothesis.

Next, we examine the relationships between FUNCINPEC and the government. The results in Table 3 shows that FUNINPEC reacts to the government across the AP, JENW, UPI, Xinhua, and All sources, while BBC, and the UBX, sources fail to show support for that hypothesis. Moreover, BBC, Xinhua, and UBX, fail to find support that the government reacts to FUNINPEC's behavior.

With regard to the relationships between KPLNF and the government, we infer from the BBC and JENW results in Table 3 that the KPLNF does not react to the government, while all the other sources support the action-reaction hypothesis. Likewise, BBC and JENW along with Xinhua would lead one to conclude that the government does not react to the KPLNF, while the other source's results would corroborate that the KPLNF' behavior Granger-causes the Cambodian government's behavior.

Finally, Table 3 reports significant Wald tests for the government Granger-causing the resistance coalition for all sources except UPI and All sources combined. Only UPI finds that the resistance coalition Granger-causes the Cambodian government. While a perusal of Table 3 will uncover many more differences across results, we will not discuss them all here.

In sum, relying on one source can cause researchers to draw biased inferences with respect to government-dissident action-reaction dynamics. This bias seems to be more pronounced in the multi-actor models than the two-actor models. We return to this issue in our conclusion and move on to analyzing the IRFs from the Indonesian VAR models.

VAR Impulse Response Function Results

The impulse response functions are used to conduct simulations where one of the variables is shocked and the response of each of the other variables is traced over a given number of time periods. Figure 1 displays the IRFs for the two-actor Indonesia VAR models. Within each larger cell, the upper left and lower right graphs indicate one actor's response to itself, while the upper right and lower left graphs indicate one actor's response to the other actor. The Y-axis represents an actor's behavior on a conflict-cooperation scale, where conflict is represented by negative values and cooperation is represented by positive values. The X-axis represents time. Each graph represents simulated responses of one actor's behavior to a hypothetical initiative (in this case a shock of unexpected cooperation) taken by one actor toward another.[16] The shaded areas are confidence bounds. When a confidence bound contains zero, we accept the null hypothesis of no impact.

[16] Each shock is set equal to one standard deviation of the orthogonalized value of the residuals for a variable in the fitted VAR model. If an actor's response is reciprocal, the moving average response curve (to a hypothetical shock of cooperation from the other actor) should be above the zero line. A curve below the zero line would indicate an inverse response pattern.

[Insert Fig. 1]

The IRFs for Indonesia are surprisingly similar. One should note that each series decays rather quickly due to the stationarity of the series. In each IRF, we see that the confidence bound contains zero after a brief number of time periods. If there is a significant response, it is positive. The positive responses support the escalatory hypothesis as opposed to the inverse hypothesis.

Observe each source's IRF in the top left and bottom right quadrants. In these instances, an actor's previous cooperation towards the other actor increase its own cooperative behavior toward that same actor in the future, though the effect dies out after one or two periods. These IRFs would corroborate the policy inertia hypothesis. All sources reveal the same general effects.

As far as the dissidents responding to the government (bottom left quadrants), we see the same effect yet much less pronounced than the dissident's effect on itself. However, there are a few more differences with respect to the effects of dissident behavior on government behavior across sources. While no IRF depicts initial responses, they all reveal a little increase after one or two periods. However, note that the confidence bounds contain zero for the UPI results. While the IRFs display similar dynamics, the increase of cooperation peaks earlier for BBC and later for Xinhua than for the other sources. In fact, the All and UBX results illustrate both the early and the late peaks as they combine information from both the BBC and the Xinhua datasets. Overall, the inferences we draw from the IRF results are surprisingly consistent across datasets. Now we draw attention towards the results from the VEC models.

VEC Results: Cointegrating Equations & Response Parameters

The first results to examine from the VEC models are the Indonesian results for the cointegrating equations. They appear in Table 4. Across all sources, the estimates illustrate that the coefficient for the cointegrated vector is negative and statistically significant as expected. Note, however, that the magnitudes of the coeficients differ across the sources.

Table 5 reports the “response parameters” for each source for Indonesia. These coefficients represent how rapidly the series return to equilibrium. If the response parameters for *?G* and *?D* are statistically significant and have opposite signs, we can infer that dissident and government behavior share a long-run equilibrium relationship. This would support the error correction/rational expectations argument that *G* and *D* move toward one another in response to a change in *d*. The results reported for every single source confirms this hypothesis. For each dataset, *?G* is negative and statistically significant and *?D* is positive and statistically significant. Moreover, the explained variance (R^2) for every model is between .39 and .46.

However, while we would detect the presence of an an error correction process in each case, the magnitude of the coefficients differ across sources. The coefficients for ?G range from -0.63 (UPI) to -0.21 (ALL), while the coefficients for ?D show less variance ranging from 0.37 (UPI) to 0.55 (JENW). That said, the models would predict that when the predictions from the cointegrating equation are positive, the dissidents are above their equilibrium value because the response coefficients for dissidents across all datasets are positive. Thus when the behavioral level of the dissidents is too high, the level of government cooperation quickly adjusts towards the dissidents at the same time that the dissidents are adjusting towards the government.

Now we turn to the Cambodian VEC results. Again, given the difficulty of specifying multiple cointegrating equations for our eight equation VECs and the fact that results are often unstable across such models, we estimate separate two-equation VEC systems for each Cambodian group's behavior toward the government and the government's behavior toward each group.

Table 6 reports the results for the cointegrating equations across each source for each VEC system. For the most part for each system, each source produces negatively signed, statstistically significant coefficients on the series' cointegrating vector. However, there are three exceptions. BBC and UPI report postive and statistically significant coefficients for the FUNINPEC to Government (?F_G) equation and JENW reports a positive and statistically significant coefficient for the KPLNF to government (?KPLNF_G) equation.

Moving to the Cambodian VEC equations of interest, Table 7 displays the coefficients for the response parameters across equations and sources. The estimates across the actors and sources are fairly consistent. For the most part, the change in the government's beghavior directed towards each dissident group is negative and statistically significant and the change in the specified dissident group's behavior directed toward the government is positive and statistically significant. Together, the results corroboate the rational expectations argument. Of the 56 estimated coeffients, there are only eight exceptions to this pattern.

To begin, for the KPLNF system of equations, AP and BBC report positive and statistically insignificant coeficients on ?KPLNF. Those same two sources report positive coefficients for ? G in the resistence coalition system of equations. BBC even reports a statistically significant coefficient. Finally, BBC and UPI produce negative and statistically significant coefficient estimates on ? FUNCINPEC for the FUNCINPEC system of equations and positive and statistically insignificant coefficient estimates on ? RESISTANCECOALITION for the RESISTANCE COALITION system of equations. Overall, the VEC reults are strikingly similar across sources.

VEC Results: Indonesia IRFs

We now discuss the VEC IRFs for the two-actor Indonesia equations. IRFs form VEC models do not always die out as they do from a stationary VAR. “Whe n the effect of a shock does not die out over time, the shock is said to be permanent,” and “when the effect of a shock dies out overtime, it is said to be transitory” (Statacorp 2005, 369). Overall, the IRFs depict that an orthogonalized shock to average government behavior directed towards the dissidents has a permanent effect on the average level of dissident behavior directed towards the government. The same relationship holds true when dissident behavior is shocked. Orthogonalized shocks to both variables yield permanent effects across all sources. For the most part an orthogonalized shock to government behavior yields a series of increases and decreases in dissident behavior but ultimately, dissident behavior increases permanently. For every source, the IRF for dissident beahvior (first and third columns in Figure 2) decreases to between 0.2 and 0.4 and then increases to between 0.4 and 0.9 and then decreases to between 0.4 and 0.7, where the line remains fairly stable after about 10 weeks.

With respect to government behavior, an orthogonalized shock to dissident behavior yields virtually an immediate permanent increase in government behavior. There are a few minor deviations from the general pattern. For example, the government IRF produced from the BBC results increases immediately like the others for the first couple periods but then sharply decreases before increasing again and remaining constant after 10 weeks.

Most of the other government IRFs immediately increase, and then descrease only slightly before maintaining stationary patterns at high levels.

Brief Discussion of Non-Reported Results

As we alluded to earlier, we produce and analyze the IRFs from the Cambodian VAR and VEC multi-actor models. However, the output is far too much to include in this paper. The VAR models across all the sources produce a total of 448 IRFs and we produced 54 IRFs for the VEC models. Here we just review the general patterns. For the most part the general IRF patterns hold across sources for the VAR models. There are observable differences though and too many to go into here. However, the vast majority of the IRFs are congruent across sources.

With respect to the Cambodian VEC IRFs, the DK system of equations and the Resistance coalition system of equations produce almost identical IRFs to the two-actor GOV-REB Indonesian VECs across both the government and rebel group variables. The DK responses decrease and increase and then return to a mid-to high stationary level after 10 weeks. Similarly, the government responses abruptly increase, slightly decrease and then remain stationary at high levels after 10 weeks.There is one exception: the government response series is transitory as opposed to permanent for the BBC results.

The major differences across sources appear in the FUNCINPEC system of equations and the KPLNF system of equations. For example, the BBC and UPI sources produce strikingly different IRFs for both the FUNINPEC IRFs and the government IRFs from the rest of the sources. The FUNINPEC series across the BBC and UPI sources well as the BBC government series are all transitory as opposed to permanent and both the UPI FUNINPEC and UPI government series yield highly variant “up and down” series. These same patterns are apparent and more pronounced in the KPLNF system of equations.

Conclusion

Overall, the inferences we draw from typical intranational conflict-cooperation statistical results are consistent across sources. However, clear differences do exist. Some sources imply that one variable Granger-causes another when many of the other sources do not. The reverse situation is true as well. Thus, we have shown that source bias can lead to researchers committing both Type 1 and Type 2 errors. Though the inferences we draw relevant to the direction of influence are often similar across results produced from different sources, the magnitudes of the coefficients and the effects (e.g., IRFs) vary across sources. Moreover, these differences appear to be more pronounced in multi-actor models and disaggregated models of government-rebel interactions.

Our recommendation to researchers is to check the robustness of findings across different data sources and combine the sources whenever it is feasible. We believe that consistent findings across sources can strengthen the validity and reliability of inferences drawn from event data studies. We also echo previous scholars like Davenport and Ball (2002) and Francisco (2006) and advocate the analysis of multiple source datasets. We contend that combining sources can help to eliminate (and/or average) the specific bias of a particular news agency and yield more accurate and reliable estimates of conflict and cooperation.

The paper also yields future work to be completed in this and related areas. Specifically, more attention should be paid to results produced from data collected from a single media source. Chances are that we could generate additional data from different sources and observe at least a few differences across the results. Second, more attention needs to be paid to the aggregation of domestic actors into collective government and dissident actors. Not only does the paper reveal that results can differ across sources, it also reveals that governments may not react and/or anticipate all rebel group's actions in the same way. Similarly, rebel groups may differ with respect to how they act, react to, and anticipate their government rival's behavior. By aggregating all rebel groups together, the potentially different relationships are masked.

In conclusion, this paper illustrates that scholars can draw different inferences from different results generated from different datasets compiled from different sources. We hope our paper cautions those working with media generated data to take the time to compile data from multiple sources and check the validity and reliability of their results across datasets generated by different media outlets.

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Table 1

A. Number of Indonesian Events Coded by Source

# of Hostile Events	AP 1985-2000	BBC 1980-2004	JENW 1992-2004	UPI 1980-2004	Xinhua 1980-2004	B,U, & X [a] 1980-2004	All [b] 1980-2004
Hostile Events (% Hostile)	8,478 (58%)	33,672 (39%)	13,098 (42%)	6,877 (53%)	20,025 (39%)	47,011 (41%)	66,270 (43%)
Total Events	14,744	85,836	30,835	13,050	51,366	114,746	154,739

B. Number of Cambodian Events Coded by Source

# of Hostile Events	AP 1985-2000	BBC 1980-2004	JENW 1992-2004	UPI 1980-2004	Xinhua 1980-2004	B,U, & X [a] 1980-2004	All [b] 1980-2004
Hostile Events (% Hostile)	4,282 (62%)	4,674 (34%)	2,463 (49%)	5,043 (61%)	6,075 (51%)	14,654 (48%)	20,830 (50%)
Total Events	6,916	13,782	4,978	8,238	12,001	30,770	41,568

[a] "B, U, & X" represents all events coded by BBC, UPI, and Xinhua with all duplicate events removed.

[b] "All" represents all events coded by AP, BBC, JENW, UPI, and Xinhua with all duplicate events removed.

Table 2

Granger Causality Tests: Indonesia (Weeks)

	AP		BBC		JENW		UPI		Xinhua		ALL		UBX	
	G	D	G	D	G	D	G	D	G	D	G	D	G	D
G	-	17.85***	-	18.02***	-	8.15*	-	7.25	-	12.23***	-	12.21***	-	12.32***
D	1.64	-	5.54	-	14***	-	1.4	-	11.60***	-	3.45	-	5.24	-
R^2	.05	.04	.43	.46	.42	.42	.42	.42	.42	.43	.42	.46	.45	.44
?^{2}	38.49***	32.81***	898***	1024***	426***	429***	866***	855***	848***	884***	842***	999***	955***	921***
N	756	756	1196	1196	609	609	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4	4	4	4	4	4	4

VAR models were run with constants and 4 lags of the variables which are not reported. *** represents statistically significant at the 1% level. ** represents statistically significant at the 5% level. * represents statistically significant at the 10% level.

Table 3
Granger Causality Tests: Cambodia (Weeks)

A: AP

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	3.52	5.07	4.00	20.53***	3.61	8.49*	4.74
DK_G	13.81***	-	2.36	1.72	4.11	13.67***	0.58	8.22*
G_FUNC	1.97	13.38***	-	18.13*	11.43**	2.85	8.62*	5.07
FUNC_G	3.68**	7.84*	43.44****	-	16.5***	9.98**	4.88	13.04***
G_KPLNF	17.99***	8.72*	1.37	46.47***	-	30.76***	0.87	25.10***
KPLNF_G	12.45***	3.77	1.79	17.86***	29.05***	-	2.32	5.82
G_RC	2.23	9.96**	10.34**	4.07*	10.77**	7.14***	-	11.39**
RC_G	6.26	1.85	8.89*	21.67***	24.16***	11.63**	4.04	-
R^2	.12	.12	.13	.18	.33	.15	.08	.12
?^{2}	98.16***	107.58***	111.22*	169.28***	365.57***	130.41***	64.06***	101.25***
N	760	760	760	760	760	760	760	760
lags	4	4	4	4	4	4	4	4

B: BBC

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	3.77	3.68	0.49	2.05	0.76	7.03	2.30
DK_G	4.60	-	6.61	3.04	17.89***	2.84	1.61	4.01
G_FUNC	2.57	3.33	-	3.45	0.89	3.33	1.66	061
FUNC_G	1.89	9.61**	0.30	-	9.59**	6.83	7.87*	1.88
G_KPLNF	2.91	21.58***	0.92	0.28	-	0.37	12.08***	2.92
KPLNF_G	10.7**	3.26	2.69	10.89***	0.26	-	11.43**	1.87
G_RC	2.43	3.03	8.20*	5.31	2.69	0.15	-	9.25**
RC_G	5.70	8.91*	2.28	2.11	13.21***	6.05	2.76	-
R^2	.04	.05	.02	.02	.03	.02	.05	.02
?^{2}	53.02***	59.7***1	26.14	28.19	46.60***	21.47	68.73***	24.08
N	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4

C: JENW

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	10.89**	0.83	3.13	11.09**	18.15***	2.42	2.22
DK_G	0.60	-	6.26	3.37	1.69	6.70	1.24	1.57
G_FUNC	0.76	9.08**	-	23.13***	0.04	12.87***	4.52	22.67***
FUNC_G	16.85***	7.22	22.90***	-	0.04	3.70	6.21	5.95
G_KPLNF	3.214	4.35	0.16	0.07	-	0.06	0.23	0.02
KPLNF_G	2.86	1.77	52.31***	12.97***	0.19	-	34.76***	2.44
G_RC	1.22	2.62	2.67	16.71***	0.13	14.61***	-	20.09***
RC_G	0.651	8.03*	7.51	6.86	0.11	0.66	0.80	-
R^2	.05	.08	.16	.11	.02	.09	.08	.08
?^{2}	33.08	51.54***	119.92***	76.17***	13.67	60.67***	50.17**	53.33***
N	613	613	613	613	613	613	613	613
lags	4	4	4	4	4	4	4	4

D: UPI

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	8.23*	2.74	4.12	4.70	7.25	12.52***	16.55***
DK_G	13.81***	-	12.73***	3.96	3.49	3.65	5.30	2.81
G_FUNC	3.06	5.01	-	10.27**	4.37	0.43	3.53	2.86
FUNC_G	3.11	1.45	11.91***	-	10.81**	10.69**	15.82***	2.84
G_KPLNF	16.55***	4.89	6.68	2.01	-	13.30***	4.04	3.69
KPLNF_G	6.75	4.73	2.48	27.83***	87.51***	-	3.67	16.77***
G_RC	21.20***	33.57***	11.94***	2.68	8.61*	7.45	-	5.72
RC_G	27.08***	4.79	1.66	3.69	15.02	1.41	15.58***	-
R^2	.14	.12	.11	.05	.31	.12	.07	.09
$?^2$	195.20***	167.46***	150.37***	66.51***	546.48***	158.37***	101.40**	113.89***
N	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4

E: Xinhua

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	7.98*	8.18*	4.45	12.38***	30.63***	4.72	1.17
DK_G	25.13***	-	6.39	21.45***	9.33**	10.79**	3.58	10.39**
G_FUNC	1.36	3.24	-	11.79**	7.90*	0.26	35.20***	8.29*
FUNC_G	1.06	6.91	3.07	-	1.28	16.75***	20.80***	23.68***
G_KPLNF	3.38	8.60*	12.66***	5.77	-	10.46**	14.10***	36.66***
KPLNF_G	3.85	5.98	3.73	3.12	6.49	-	7.53	3.65
G_RC	7.71*	6.74	3.89	1.27	1.81	13.41***	-	20.37***
RC_G	11.7	10.81**	14.91***	8.09*	3.13	7.50	5.08	-
R^2	.07	.31	.06	.15	.05	.14	.09	.12
$?^2$	90.67***	529.38***	67.25***	212.06***	62.23***	197.79***	123.66***	163.59***
N	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4

F: UBX

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	16.78***	6.44	13.27***	2.41	3.61	2.07	1.53
DK_G	42.77***	-	3.92	5.59	10.79**	8.83*	1.92	10.9**
G_FUNC	3.34	.63	-	4.19	6.94	.465	3.30	2.69
FUNC_G	5.21	11.75**	3.22	-	8.94*	8.96*	6.21	6.36
G_KPLNF	12.49**	14.55***	5.22	2.63	-	7.62*	5.98	14.37***
KPLNF_G	10.40**	10.43**	3.41	1.48	25.19***	-	5.67	5.68
G_RC	1.35	0.77	1.56	8.10*	2.48	9.09*	-	11.43**
RC_G	4.73	6.70	6.04	8.41*	10.37**	12.15***	7.2548	-
R^2	.13	.30	.04	.11	.13	.11	.08	.10
$?^2$	173.96***	490.75***	43.91*	147.00***	185.60***	145.64***	103.59**	131.24***
N	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4

G: All Sources Combined

Independent Variables	Dependent Variables							
	G_DK	DK_G	G_FUNC	FUNC_G	G_KPLNF	KPLNF_G	G_RC	RC_G
G_DK	-	*12.37****	2.76	16.06***	4.02	4.88	2.09	0.56
DK_G	*36.85****	-	5.30	6.88	15.27***	13.89***	3.79	14.34***
G_FUNC	1.52	1.15	-	*8.67**	6.61	1.35	10.14**	3.68
FUNC_G	10.00**	13.78***	*9.51****	-	5.17	9.32	11.86**	6.95
G_KPLNF	11.28**	13.87***	4.28	1.38	-	*17.6****	7.95*	21.65***
KPLNF_G	5.21	6.82	1.91	6.25	*7.62**	-	5.21	8.71*
G_RC	2.53	0.66	1.57	8.39*	2.67	11.71***	-	*5.32*
RC_G	12.94***	8.23*	3.54	6.64	20.29***	6.64	*6.72*	-
R^2	.12	.24	.04	.12	.22	.10	.08	.09
?^{2}	159.32***	373.88***	44.34*	168.61***	335.71***	139.26***	103.95***	123.40***
N	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4

VAR models were run with constants and 4 lags of the variables which are not reported. *** represents statistically significant at the 1% level. ** represents statistically significant at the 5% level. * represents statistically significant at the 10% level.

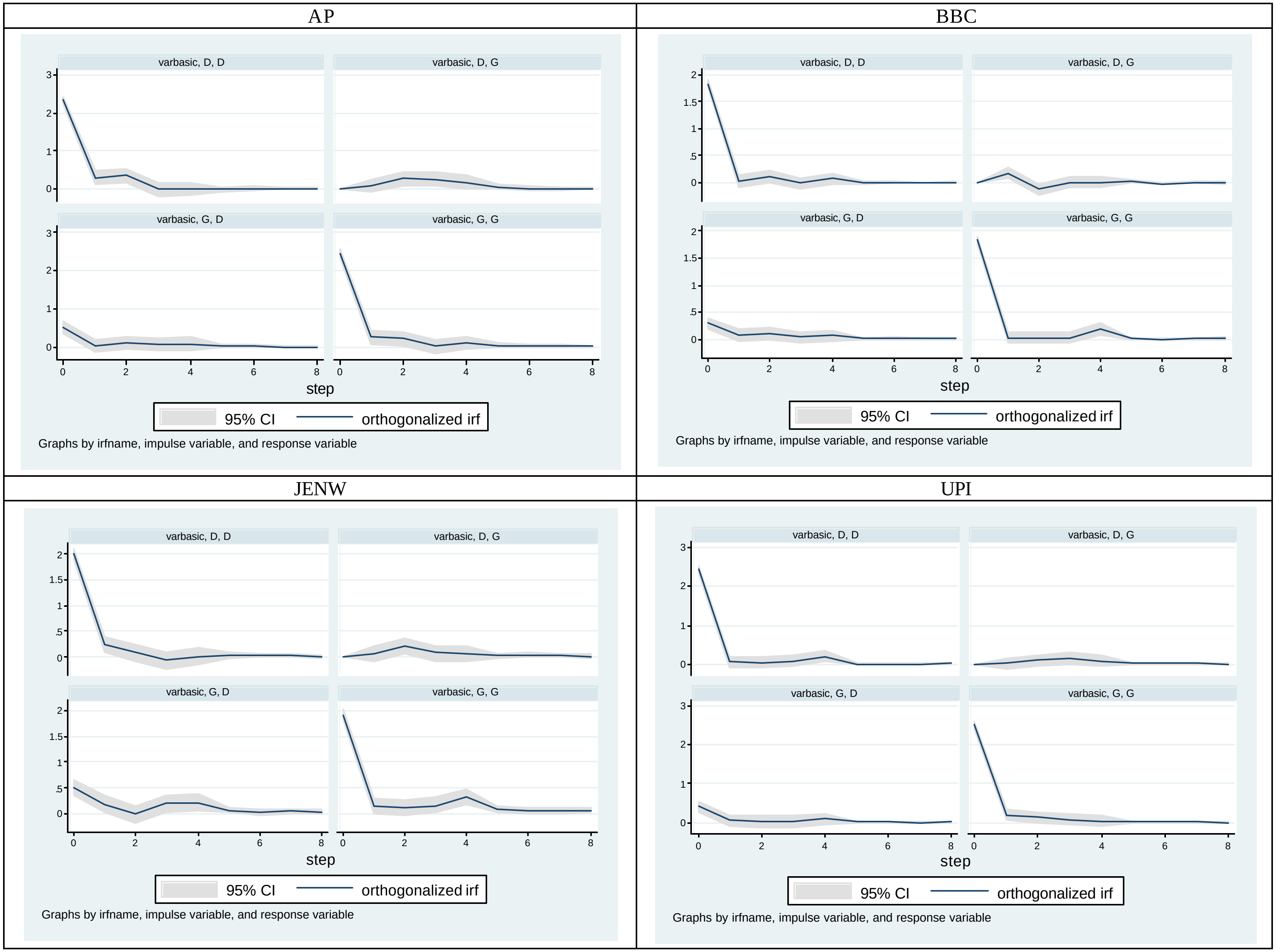
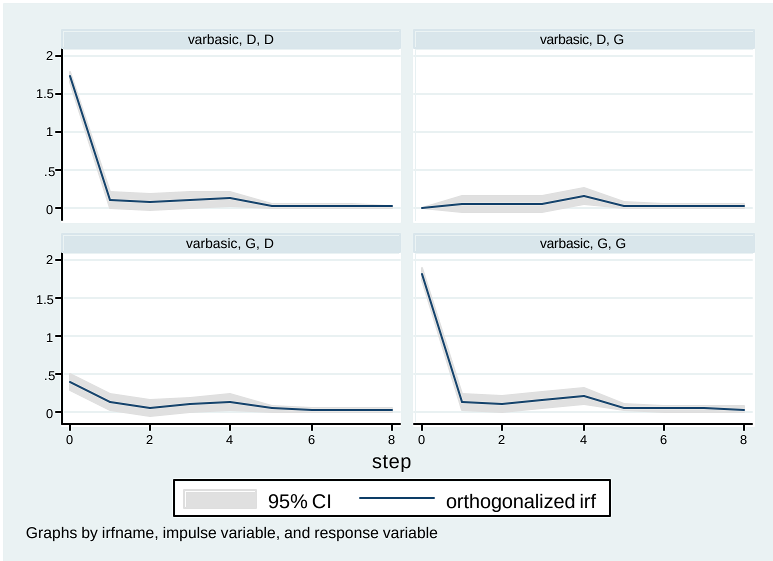


Figure 1 VAR Impulse Response Functions: Indonesia (Weeks)

Xinhua



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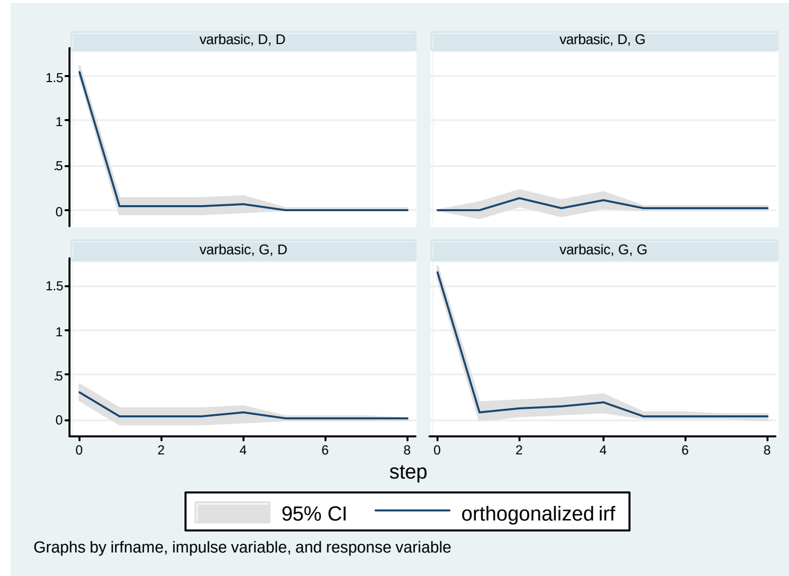


UPI, BBC, & Xinhua

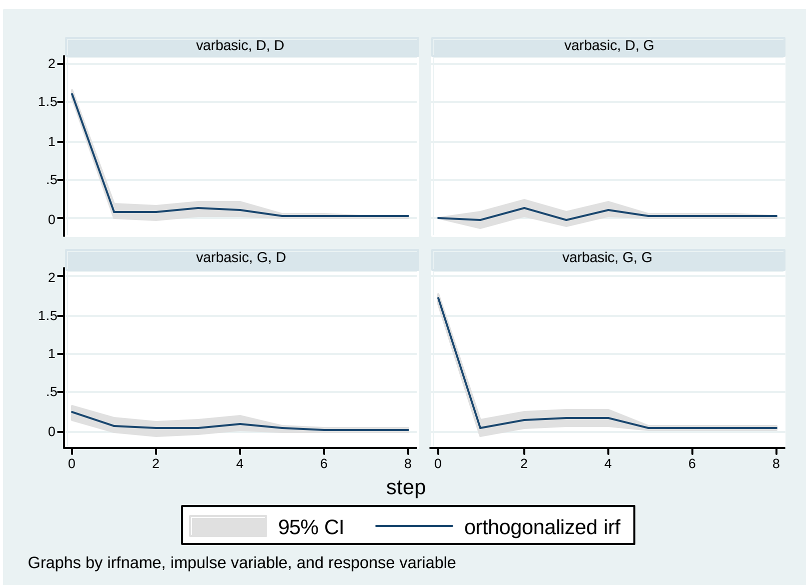


Figure 1 Continued VAR Impulse Response Functions : Indonesia (Weeks)

Table 4
Cointegrating Equations: Indonesia (Weeks)

	AP	BBC	JENW	UPI	Xinhua	All	UBX
Cointegrating Equation	d	d	d	d	d	d	d
G	1.0	1.0	1.0	1.0	1.0	1.0	1.0
D	-1.12***	-1.35***	-1.43***	-0.81***	-1.21***	-1.82***	-1.28***
	(.085)	(.087)	(.105)	(.069)	(.077)	(.109)	(.091)

Models were run with constants which are not reported.

Table 5
VEC Adjustment Parameters: Indonesia (Weeks)

	AP		BBC		JENW		UPI		Xinhua		All		UPI, BBC, & Xinhua	
	?G	?D	?G	?D	?G	?D	?G	?D	?G	?D	?G	?D	?G	?D
d	-0.49***	0.43***	-0.26***	0.51***	-0.22***	0.55***	-0.63***	0.37***	-0.37***	0.45***	-0.21***	0.40***	-0.33***	0.41***
	(.054)	(.052)	(.041)	(.039)	(.051)	(.053)	(.049)	(.050)	(.043)	(.041)	(.032)	(.030)	(.039)	(.037)
R^2	.39	.30	.43	.46	.42	.42	.42	.42	.42	.43	.42	.46	.45	.44
?^{2}	502***	457***	898***	1024***	426***	429***	866***	855***	848***	884***	842***	999***	955***	921***
N	756	756	1196	1196	609	609	1196	1196	1196	1196	1196	1196	1196	1196
lags	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Models were run with constants and 4 lags of the differenced variables which are not reported. Though we note that all lags of the differenced variables were negative and usually statistically significant. Parentheses contain the standard errors. *** represents statistically significant at the 1% level.

Table 6
Cointegrating Equations: Cambodia (Weeks)

	AP	BBC	JENW	UPI	Xinhua	UBX	All
Cointegrating Equation	d	d	d	d	d	d	d
? G_DK	1.0	1.0	1.0	1.0	1.0	1.0	1.0
? DK_G	-0.58***	-1.45***	-0.72***	-1.08***	-0.26***	-0.56***	-0.57***
	(.056)	(.099)	(.089)	(.072)	(.026)	(.035)	(.039)
? G_F	1.0	1.0	1.0	1.0	1.0	1.0	1.0
? F_G	-0.63***	2.45***	-1.27***	7.65***	-0.15***	-0.18***	-0.30***
	(.056)	(.153)	(.107)	(.779)	(.024)	(.030)	(.035)
? G_KPLNF	1.0	1.0	1.0	1.0	1.0	1.0	1.0
? KPLNF_G	-0.32***	-2.39***	0.30**	-2.70***	-0.49***	-0.87***	-1.46***
	(.095)	(.153)	(.132)	(.779)	(.078)	(.056)	(.087)
? G_RC	1.0	1.0	1.0	1.0	1.0	1.0	1.0
? RC_G	-9.12***	-1.80***	-1.83***	-0.59***	-0.61***	-0.99***	-1.19***
	(.651)	(.153)	(.141)	(.059)	(.055)	(.075)	(.090)

Models were run with constants which are not reported.

Table 7
VEC Adjustment Parameters: Cambodia (Weeks)

A: AP

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	? G	? D	? G	? D	? G	? D	? G	? D
d	-0.65***	0.40***	-1.02***	0.49***	-0.54***	0.06	-0.00	0.09***
	(.059)	(.078)	(.082)	(.111)	(.039)	(.051)	(.039)	(.007)
R^2	.45	.35	.57	.36	.36	.45	.37	.44
?^{2}	611***	397***	985***	414***	415***	600***	444***	594***
N	756	756	756	756	756	756	756	756
lags	4	4	4	4	4	4	4	4

B: BBC

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	? G	? D	? G	? D	? G	? D	? G	? D
d	-0.32***	0.40***	-0.11***	-0.36***	-0.01	0.43	0.0009***	0.005***
	(.059)	(.078)	(.018)	(.021)	(.05)	(.063)	(.0003)	(.000)
R^2	.40	.44	.42	.49	.58	.54	.36	.51
?^{2}	800***	919***	844***	1141***	1506***	1323***	676***	1219***
N	1196	1196	1196	1196	1171	1171	1196	1196
lags	4	4	4	4	29[a]	29[a]	4	4

[a] The model would only estimate with 29 lags due to multicollinearity.

C: JENW

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	? G	? D	? G	? D	? G	? D	? G	? D
d	-0.51***	0.48***	-0.36***	0.52***	-0.84***	-1.63**	-0.26***	0.46***
	(.068)	(.072)	(.055)	(.050)	(.360)	(.798)	(.064)	(.044)
R^2	.42	.40	.40	.41	.53	.60	.43	.48
?^{2}	432***	405***	394***	417***	452***	625***	444***	550***
N	609	609	609	609	545	545	609	609
lags	4	4	4	4	68[a]	68[a]	4	4

[a] The model would only estimate with 68 lags due to multicollinearity.

D: UPI

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	? G	? D	? G	? D	? G	? D	? G	? D
d	-0.38***	0.41***	-.05***	-0.15***	-0.01	0.27***	-0.61***	0.36***
	(.042)	(041)	(.014)	(041)	(.012)	(.019)	(.046)	(.055)
R^2	.40	.40	.52	.52	.21	.37	.42	.39
?^{2}	805***	785***	1266***	1272***	326***	710***	880***	749***
N	1196	1196	1187	1187	1196	1196	1196	1196
lags	4	4	13[a]	13[a]	4	4	4	4

[a] The model would only estimate with 13 lags due to multicollinearity.

E: Xinhua

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	?G	?D	?G	?D	?G	?D	?G	?D
d	-1.00***	0.14**	-1.03***	0.42***	-0.68***	0.36**	-0.66***	0.40**
	(.058)	(.073)	(.058)	(.100)	(.125)	(.188)	(.050)	(.054)
R^2	.50	.44	.51	.44	.54	.48	.46	.38
$?^2$	1171***	921***	1210***	932***	1342***	1005***	1009***	722***
N	1196	1196	1196	1196	1168	1168	1196	1196
lags	4	4	4	4	32 [a]	32 [a]	4	4

[a] The model would only estimate with 32 lags due to multicollinearity.

F: UPI, BBC, & Xinhua

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	?G	?D	?G	?D	?G	?D	?G	?D
d	-0.80***	0.39***	-0.94***	0.35***	-0.31***	0.61***	-0.39***	0.43***
	(.055)	(.056)	(.056)	(.093)	(.037)	(054)	(.040)	(041)
R^2	.48	.41	.49	.42	.39	.39	.45	.41
$?^2$	1089***	840***	1149***	846***	742***	758***	964***	825***
N	1196	1196	1196	1196	1168	1168	1196	1196
lags	4	4	4	4	4	4	4	4

G: All Sources

	DK		FUNCINPEC		KPLNF		Resistance Coalition	
	?G	?D	?G	?D	?G	?D	?G	?D
d	-0.74***	0.41***	-0.84***	0.44***	-0.09***	0.49***	-0.32***	0.39***
	(.052)	(.055)	(.054)	(.080)	(.025)	(.035)	(.036)	(.036)
R^2	.47	.39	.47	.44	.32	.43	.42	.40
$?^2$	1066***	767***	1068***	925***	569***	885***	845***	812***
N	1196	1196	1196	1196	1168	1168	1196	1196
lags	4	4	4	4	4	4	4	4

Models were run with constants and 4 lags of the differenced variables which are not reported. Though we note that all lags of the differenced variables were negative and mostly statistically significant. Parentheses contain the standard errors for the response parameters. *** represents statistically significant at the 1% level. ** represents statistically significant at the 5% level.

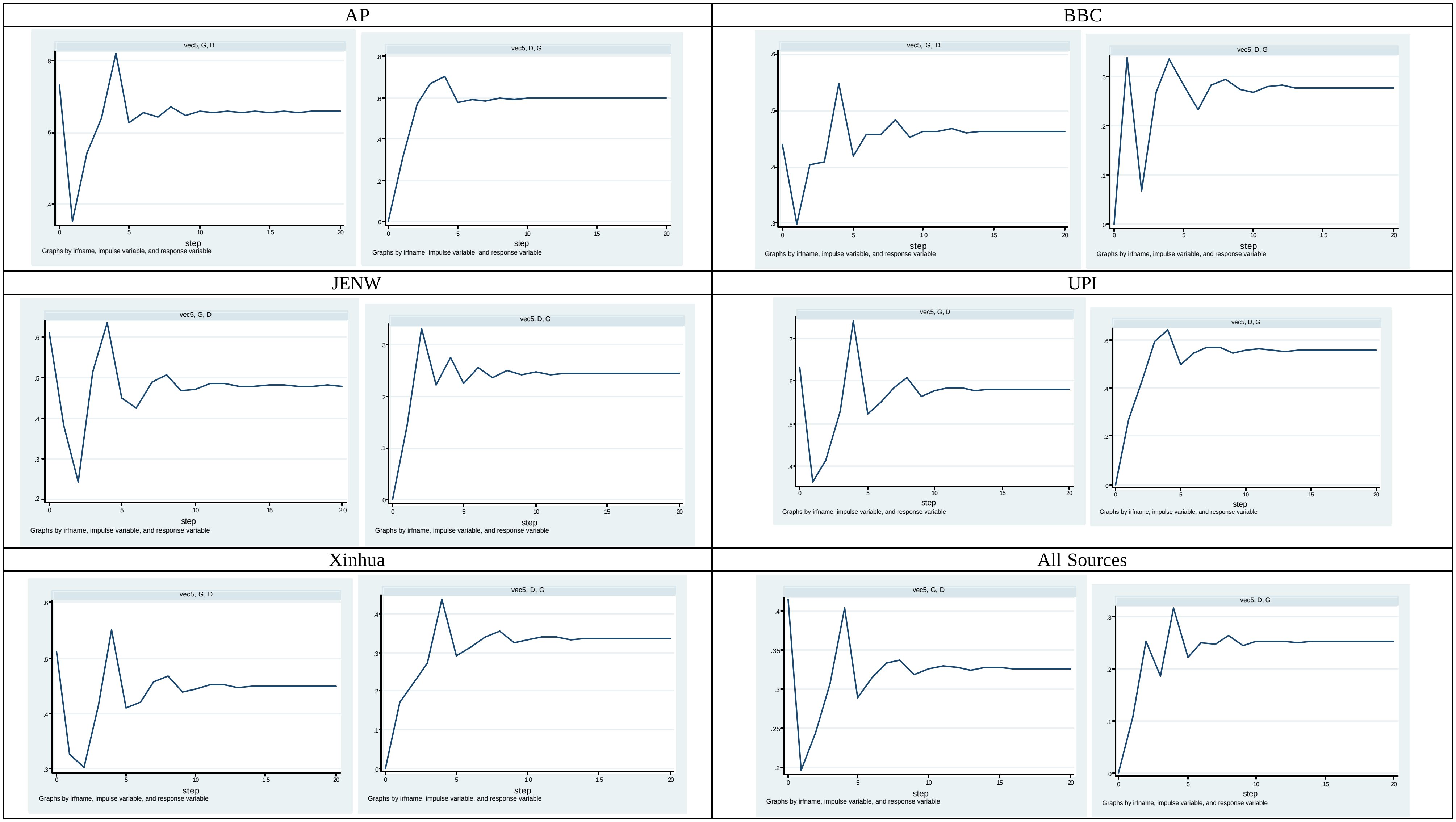
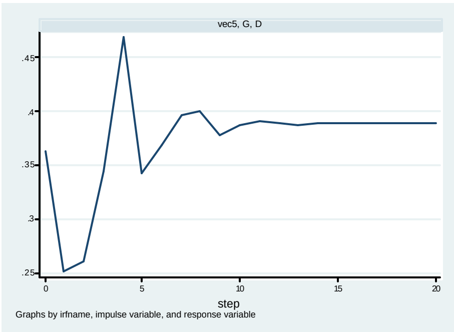


Figure 2 Continued VEC Impulse Response Functions: Indonesia (Weeks)

UPI, BBC, & Xinhua	



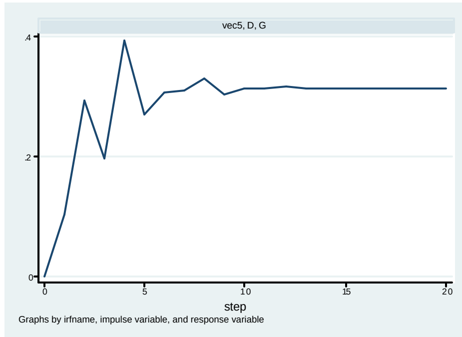


Figure 2 Continued VEC Impulse Response Functions: Indonesia (Weeks)