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What Explains Changes in the Level of Abuse Against Civilians during the Peruvian Civil War?

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Abstract

Using a new monthly time-series data set, we explore the factors associated with variations in the number of civilians killed or wounded by participants in the civil war in Peru during the 1980s and 1990s. We find that an increase in the level of abuse by one side is strongly associated with subsequent increases in the level of abuse by the other. Certain types of foreign intervention have a large and statistically significant impact on the level of abuse; some types of intervention raise the level of violence, but others reduce it.

Key words: Peru, civil war, conflict, abuse against civilians

1. Introduction

In 2003, the Peruvian Truth and Reconciliation Commission (TRC) reported on twenty years of abuse of civilians during the civil war period (1980-2000). The Peruvian civil war began in the early 1980s with attacks on civilians and government targets by the *Partido Comunista del Perú – Sendero Luminoso*, a Maoist group originating as a student movement based in Peru's universities. *Sendero Luminoso* (SL) was founded in the 1960s by a former philosophy professor, Abimael Guzmán, who remained in control of the organisation for most of the civil war. In 1980, when elections were held in Peru for the first time in 12 years, SL began a violent campaign against the government by burning ballot boxes in a small town in the rural highland region of Ayacucho. Over the next two years, SL increased its range of violent activity in Ayacucho and in the neighboring regions of Huancavelica and Apurímac, taking control of isolated villages and killing local officials and other 'collaborators'.

Initially, government leaders appear not to have regard SL as a serious threat, believing that the police force alone could deal with the rebels. However, there was a gradual increase in the level of SL activity during 1981, and at the end of December emergency laws were introduced in the regions where SL was active. Government military forces were granted extensive arbitrary powers, and were soon reported to be participating in the torture, rape and murder of villagers who were difficult to distinguish from the rebels who lived among them. By the end of 1982, SL had formally engaged on Stage II of its revolutionary plan, the 'protracted people's war', and both sides in the conflict had begun to kill large numbers of non-combatant civilians.

The civil war continued over the next decade, fought mainly in rural highland areas, but also occasionally in large cities. At the peak of the violence in the late 1980s, there were several hundred civilian conflict deaths every month. The main participants in the war were regular government police and army units, the *Ejército Guerrillero Popular* and other pro-government paramilitary groups, and SL. In some areas, a small part of the violence was due to a second armed rebel group, the *Movimiento Revolucionario Túpac Amaru*, but they accounted for less than 2% of fatalities. A similarly small fraction of the violence was due to the *rondas campesinas*, which were government-armed village self-defense groups.

Throughout most of this period, Peru was a parliamentary democracy, but many parts of the state forces operated independently of the elected government. In April 1992, the elected president, Alberto Fujimori, instigated a coup d'état against the legislature. The Peruvian congress was dissolved, the constitution was suspended and many senior judges were removed from office. One of the stated aims of the coup was to give government forces a freer hand in suppressing insurgency. Then in September 1992, police captured Guzmán, who had been hiding in a house in Lima. After Guzmán's capture, the leadership of SL became fragmented. Early in 1993, Fujimori introduced a 'repentance law', offering an amnesty to SL leaders who surrendered and co-operated with the government; over 5,000 rebels made use of the amnesty over the next two years. Individual SL cells continued fighting, but by the late 1990s monthly civilian conflict fatalities had fallen to single figures, and the war was effectively over.

Like many other civil wars, the Peruvian conflict involved a large number of civilian casualties. The war was not an ethnic conflict, and none of the forces perpetrating violence against civilians had a genocidal motive; yet both sides consistently employed terror against civilians. Understanding why civilians are targeted in this type of conflict is a focus of much current research. Many papers, some of which are discussed in the next section, explore cross-sectional variation in conflict data in order to shed light on the factors that make violence against civilians more likely in particular areas or among particular groups of people. This literature has produced many valuable insights, but it does not address questions about the reasons why violence against civilians flares up or dies down in the middle of an ongoing conflict. In order to address such questions about the dynamics of violence, we need to analyze the variation in time-series conflict data. This paper presents newly constructed time-series data relating to the civil war in Peru, based on data published by the TRC. Analysis of the data reveals a strong 'cycle of violence' in which each side responds in kind to violence perpetrated by the other. We are able to show which types of foreign intervention help to break the cycle of violence, and which exacerbate it.

The next section reviews the existing literature on civilian abuse and civil war, which informs a number of specific hypotheses about the factors driving variations in the level of abuse over time. Section 3 presents the data that we use to test these hypotheses, and Section 4 our results.

2. Conflict Intensity, Civilian Abuse and Foreign Intervention

2.1. Determinants of the level of civilian abuse

The existing literature on civilian abuse focuses on the factors that explain the cross-sectional variation in the level of violence, either at the national level (what sort of civil war entails a large amount of abuse), or the regional level (what sort of village sees a large amount of abuse). Formal theoretical models of civil war participants' decisions focus on the national level. For example, Azam and Hoeffler (2002) present a model in which an incumbent government has an incentive to terrorize some of its civilians and force them to flee their homes. The population displacement disrupts either the rebels' economic base or their recruitment base, and is a precursor to a conventional military offensive by the government. In equilibrium, more abuse is likely when the government has more resources net of the cost of conventional fighting, and when the rebels are in a stronger position *ex ante*. Bueno de Mesquita and Dickson (2007) present a model in which the rebels may have an incentive to terrorize civilians if this provokes the government to do the same. The government response may reveal the value it places on the welfare of its citizens, and if this value is low then rebel support among the population may be strengthened. However, a separating equilibrium is not guaranteed, and there exist pooling equilibria in which rebel abuse leads governments of all types to choose the same level of abuse, which could be high or low.

It is difficult to find statistical evidence that relates directly to the structure of such game-theoretical models, but the empirical study of Valentino *et al*. (2004) indicates that government abuse of civilians represents a deliberate military strategy. Using national level data on the incidence of mass killings, they show that high civilian casualties are more likely when the rebels receive active support from the local people, or when the rebels represent a serious threat to the incumbent regime. Moreover, the results of Eck and Hultman (2007) indicate that government preferences play a role in determining the level of abuse. Using data on the number of civilian casualties, they show that on average, a high level of abuse by the government is more likely when the government is autocratic, but a high level of abuse by the rebels is more likely when the government is democratic. Further, using cross-sectional data on the number of refugees from civil wars, Azam and Hoeffler (2002) provide evidence for several economic effects that are consistent with their game-theoretical model. For example, as predicted, higher levels of aid to a country – interpreted as a component of government resources – are associated with a larger number of refugees.

A related empirical literature[1] investigates the determinants of regional variation in the level of civilian abuse in particular civil wars. One common feature of many conflicts is that civilian casualties are more likely in regions where neither side has unequivocal support, and that political and ethnic minorities are safer when they are small minorities. Evidence for such a pattern appears in Balcells' (2007) study of the Spanish Civil War, Bundervoet's (2009) study of Burundi, de la Calle Robles' (2007) study of the Basque Country, Humphreys

[1] These papers are part of a growing body of research on the microeconomics of civil wars; see Verwimp *et al*. (2009).

and Weinstein's (2006) study of Sierra Leone, and Kalyvas and Kocher's (2009) study of Vietnam. This evidence reinforces the idea that abuse of civilians is often a deliberate military strategy, focussed on areas where the contest for control is fiercest. Lyall (2009) presents evidence from Chechnya showing that campaigns of violence against civilians do sometimes create a military advantage.

Several of the papers cited above also indicate that there is an economic incentive for civilian abuse. Everything else being equal, troops target wealthier civilians, either in an attempt to inflict maximum economic damage on the population, or just to acquire loot. This suggests that some types of foreign economic intervention may affect the level of civilian casualties. With the exception of Azam and Hoeffler (2002), no paper looks directly at the link between civilian casualties and foreign aid, but there is a related literature on the impact of foreign economic intervention on the propensity of a country to engage in civil war.

2.2 Foreign economic intervention and civil wars

Foreign aid could affect both the probability that a war will start and its duration[2] once started. Some of the possible channels for these effects are outlined in Collier and Hoeffler (2002). Aid may make peace more likely by strengthening government forces relative to the rebels (even if this involves more government abuse of civilians in the short run), or by increasing the opportunity cost of fighting. The higher opportunity cost could result from improved economic performance, better male education, or a change in relative prices that reduces the real value of lootable export commodities.[3]

The evidence on foreign economic intervention is mixed. For example, Regan (2002) and Regan and Aydin (2006) find a *positive* association between intervention and the duration of civil wars. Similarly, Collier and Hoeffler (2007) find that foreign aid leads to higher levels of government military expenditure, and that this *increases* the probability that a civil war will start. On the other hand, Collier *et al.* (2004) find no statistically significant relationship between civil war duration and economic intervention. Using a dynamic panel data model, de Ree and Nillesen (2009) model civil war onset and civil war duration simultaneously. They find that foreign aid has no significant impact on the probability that a civil war will start, but increases the probability that it will end, once started. Arguably, their simultaneous treatment of onset and duration make these results the most robust. However,

[2] In this section we focus on papers that directly examine the link between civil war duration and foreign economic intervention. These are part of a larger literature on civil war duration surveyed by Hegre (2004).

[3] That is, aid might have a 'Dutch Disease' effect; see Younger (1992).

taken as a whole, the results from cross-section and panel data studies are inconclusive. One possible reason for this ambiguity is that the impact of aid on civil wars depends on country-specific economic characteristics. One key characteristic is the availability of lootable resources, in particular gems and narcotics.

2.3 Narcotics and conflict

Lootable resources may create a rent-seeking motive for civil war (Collier and Hoeffler, 2004); even in the presence of other motives, such resources may provide rebels with a reliable source of funds. Coca and opium crops represent an extreme case, because rebels are likely to find them easier to exploit than does the incumbent government, which risks losing international legitimacy by trading narcotics. Cornell (2005) points out that 14% of the intrastate conflicts listed in the Uppsala Conflict Data Project occur in the 5% of countries which have substantial coca or opium exports. In these countries, it is very unusual to find rebel organisations *not* involved in the narcotics trade. Moreover, evidence suggests that the presence of narcotics increases civil war duration, everything else being equal (Ross, 2004a,b; Fearon, 2004).

The role of coca in funding the activity of SL is documented by Kay (1999), Palmer (1992) and Tarazona-Sevillano and Reuter (1990). In areas such as the Upper Huallaga Valley, SL operated as a middleman, running airstrips in remote locations and charging landing fees for planes transporting the coca crop to Colombia for processing. Estimates of coca production in rebel regions during the civil war are rather imprecise, but suggest that the extent of production was correlated with conflict intensity. For example, it is estimated that the area under coca cultivation in Peru fell from around 100,000 hectares in 1992-1995 to around 40,000 hectares by the end of the decade. In cross-country studies of the civil war duration and narcotics production, Peru represents an observation very close to the regression line.

However, with no time-series analyses of the conflict in Peru, and only a handful of time-series analyses of other conflicts, we know very little about the effect of variations in the availability of lootable resources, or in other economic incentives, on the rebel or government war effort. Similarly, we know little about how such variations might affect the propensity of either side to engage in civilian abuse. Before describing the data that we will use to address this gap in the literature, we present the main hypotheses that we wish to test.

2.4 Hypotheses concerning the Peruvian conflict

There is consistent evidence from around the world that civilian abuse is often a conscious military strategy, most frequently observed in locations where neither side in the conflict has an overwhelming military advantage. Taken together, theoretical papers exploring such strategies indicate that *either* an increase the extent of civilian abuse *or* some other sign of strength by the side that is initially weaker (the rebels) may be successful in provoking more abuse by the other side (the government). Such activity is likely to require a greater overall military effort by the government. This leads to our first hypothesis.

H1. Increases in both the total level of conflict effort and in the extent of civilian abuse by the rebels (SL) will be associated with subsequent increases in the total level of conflict effort and in the extent of civilian abuse by the Peruvian government.

In some of the existing theoretical literature, abuse by government forces is regarded as a strategy to weaken the rebels, and there is evidence of the success of such a strategy in places such as Chechnya. The effectiveness of such a strategy in Peru is open to question. Authors such as Taylor (1998) discuss anecdotal evidence that the killing of civilians suspected of rebel sympathies in a government-controlled village was often followed by the killing of civilians suspected of government sympathies the next time the village changed hands. Nevertheless, we can explore the following hypothesis.

H2. Increases in both the total level of conflict effort and in the extent of civilian abuse by the Peruvian government will be associated with subsequent reductions in the total level of conflict effort and in the extent of civilian abuse by the rebels.

Our other hypotheses concern economic factors that might affect conflict intensity, particularly economic interventions by the US and other foreign governments. The evidence on the relationship between foreign aid and conflict intensity is mixed. However, arguments that foreign aid will increase government military spending and so raise conflict intensity often refer to the fungibility of aid. Fungibility means that a militaristic government can respond to an increase in, for example, aid for health or education programs by reducing its own health and education expenditure, facilitating more military spending while keeping health and education provision constant. Evidence suggests that aid is not entirely fungible (Feyzioglu *et al*., 1998), and a positive association between general aid and government military spending does not necessarily entail a high level of fungibility, because the different components of aid to a given country in a given year (health aid, education aid, military aid) might be positively correlated. If we control for the level of military aid, then we might well be able to identify a clear negative link between general aid and conflict intensity, as such aid raises productivity and increases the opportunity cost of fighting. We consider the following two hypotheses.

H3. Increases in military aid raise the total conflict effort and the extent of civilian abuse by the government.

H4. Increases in general aid reduce the total conflict effort and the extent of civilian abuse by the government and rebels.

Testing hypotheses about the link between coca revenue and conflict intensity is more difficult, because reliable high-frequency time-series data on coca production and coca prices is not available for Peru. However, one reliably documented statistic is the amount of US aid to Peru dedicated to disrupting the coca trade. If such aid is effective, it will increase the rebels' opportunity costs. Moreover, by investing Peruvian police with human capital specific to counter-narcotics activity, it may influence the deployment of government forces at the margin.[4] Counter-narcotics operations do not typically involve the forced relocation of large numbers of people, so this may reduce the extent of government abuse of civilians. Our fifth hypothesis is as follows.

H5. Increases in counter-narcotics aid reduce the extent of civilian abuse by the government and rebels.

A final hypothesis concerns the effect of inflation on conflict intensity. Between 1988 and 1991 (when a new currency was introduced), Peru experienced annual consumer price inflation rates of well over 100%. During this hyperinflationary period, public sector wage increases often lagged behind price increases, and the real value of wages paid in Peruvian currency was very uncertain. This may have worsened recruitment and desertion problems for government forces, so our final hypothesis is as follows.

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[4] A complicating factor is that counter-narcotics aid may be partly fungible, because police trained for counter-narcotics operations can also be used to attack rebels in areas not associated with coca production. A US General Accounting Office Report to Congress (GAO/NSIAD-92-36; B-245527) estimates that only 56% of Peruvian police trained with US counter-narcotics resources were used in coca eradication missions; the rest were used for general counter-insurgency. In this case, the net impact of counter-narcotics aid on conflict intensity is uncertain.

H6. Increases in inflation reduce the extent of civilian abuse by the government.

The rebels, relying from coca revenue in US Dollars, are unlikely to have been directly affected by inflation in local currency prices.

3. Data on the Peruvian Conflict

3.1 Data on civilian abuse and conflict intensity

Our primary source of data is the TRC. Between 2001 and 2003, the TRC interviewed just under 17,000 witnesses to violent events in Peru during the period 1980-2000; the TRC's final report appears in Corazao *et al*. (2003). TRC transcripts provide information about individual violent conflict events, including the time and location of the event, which military group initiated it (for example, a regular government police or army unit, a government-funded paramilitary group, or SL), how many members of each group were killed or injured, and how many civilians were killed or injured. These data have been collated by the Conflict Analysis Resource Center (www.cerac.org.co), and published as the *Peru Conflict Database V1*. Ball *et al*. (2003) provide an overview of the TRC data, and compare them with data from alternative sources, such as the National Coalition of Human Rights, the Human Rights Commission, and the Defender of the People (a government ministry). None of the data sources is entirely free from measurement error. However, Ball *et al*. conclude that the TRC documented the broadest range of perpetrators of violence, and that it is the most comprehensive and consistent source of information about the conflict. Other organisations, which collected data contemporaneously, were not able to conduct surveys when the conflict was most intense. Moreover, they were concerned principally with human rights violations by government forces, and appear to have substantially under-reported violence by rebel groups.

Some of the cross-sectional variation in the database has already been analyzed; see for example Castillo and Petrie (2007) and León (2009). However, we are interested in the time-series variation. By aggregating individual observations in the database, we are able to construct monthly observations for the following quantities: the number of conflict events initiated by regular government forces or paramilitaries (government / paramilitary attacks),[5] the number initiated by rebel forces[6] (rebel attacks), the number of civilians killed or injured

[5] Paramilitaries account for about 9% of government-funded attacks and about 12% of civilians killed by government-funded forces.

[6] Since *Sendero Luminoso* attacks make up over 98% of all rebel attacks, it makes little difference to the time series whether other rebel groups are included. In the figures discussed below, they are included.

in government / paramilitary attacks, the number killed or injured in rebel attacks, and the number of civilians detained by government forces in any type of event. In most cases, it is unclear from the database what eventually happened to those who were detained, but we interpret total detentions as an approximate estimate of the number of 'disappearances'.

Totals for each of the series are listed in Table 1. One complication is that some of the conflict events are not dated precisely enough to allocate them to a particular month: we know only the year in which they happened. Such events account for 20% of all government / paramilitary attacks and 5% of all rebel attacks. In the results reported below, these annual observations are included in the following way. Let x_t be the total number of observations of a particular dimension of the conflict (for example, rebel attacks) in month t. Let x_y be the total number of annual observations for that year ($t \in y$), and let $x_s = \Sigma_{t \in y} x_t$. In other words, x_s is the sum of all monthly observations over the year. Our preferred measure of conflict intensity for month t is $x_t' = [1 + x_y / x_s] \cdot x_t$. That is, we scale our original monthly observations by the ratio of total observations for the year to total monthly observations. In other words, we allocate the observations that cannot be dated precisely in proportion to the relative level of conflict intensity apparent in the monthly data. In the appendix, we explore the consequences of modeling the conflict using x_t instead of x_t'; this turns out to make very little difference to our results.

The five x_t' time series are depicted in Figure 1 for the period January 1980 – December 2000. We regard the number of civilian casualties caused by either side as an index of the intensity of their abuse of civilians, and the number of attacks as an index of their overall conflict effort. The number of civilian detentions measures a separate and distinct dimension of the government's abuse of civilians. It can be seen that there is some positive correlation between the different series: for example, they all peak in the middle of 1984. However, the correlation is far from perfect, and the different series do represent separate and distinct dimensions of conflict intensity.

3.2 Data on the correlates of conflict intensity

Hypotheses H3-H5 relate to the effect on conflict intensity of different types of aid: general development aid, military aid, and counter-narcotics aid. General development aid is measured as the total amount of overseas development assistance from OECD countries to

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However, attacks by members of the *rondas campesinas* are excluded. The *ronderos* represent a third side in the conflict, but are responsible for only 3% of the attacks and 2% of the casualties in the TRC database. Despite their importance in other respects, the *ronderos* were not significant perpetrators of violence.

Peru in deflated millions of US Dollars, as reported in the OECD Development Assistance Committee database (www.oecd.org/dac). Figures for military aid and counter-narcotics aid, also measured in deflated millions of US Dollars, are taken from the US Overseas Loans and Grants database (the Greenbook, www.usaid.gov/policy/greenbook.html). These data exclude military aid from other OECD countries, but such aid is likely to represent a very small fraction of the total. The different aid series are shown in Figure 2. These data are reported only on an annual basis; in our monthly dataset, the observation for month t will be the level of aid in the whole year including month t.

Hypothesis H6 relates to the effect on conflict intensity of consumer price inflation. A monthly Peruvian consumer price index is reported in the International Monetary Fund International Financial Statistics database (www.imfstatistics.org). Our measure of inflation in month t is the rate of growth of this index in the 12 months up to t; this series is also shown in Figure 2.[7]

4. Modeling the Conflict

4.1 Data transformations

All five of the conflict series in Figure 1 have distributions that are highly skewed, with a few very large observations in the right-hand tail of the distribution. When we try to fit a linear model to the data in Figure 1, we end up with regression residual distributions that are highly skewed and fat-tailed. Small changes in sample size lead to large changes in estimated parameter values, suggesting that a linear model is not robust. For this reason, we work with logarithmic transformations of the series, which are depicted in Figure 3. The series are defined a follows.

pgi_t	the logarithm of government / paramilitary attacks in month t
pgk_t	the logarithm of the number of civilians killed or injured in government / paramilitary attacks in month t
rbi_t	the logarithm of rebel attacks in month t
civ_t	the logarithm of the number of civilians detained in month t
rbk_t	the logarithm of the number of civilians killed or injured in rebel attacks in month t

[7] The growth rate is measured as the change in the logarithm of the index. It is also possible to construct a month-on-month inflation series, but this series is highly volatile, and does not capture the hyperinflationary period around 1990 as starkly as the annual inflation series in Figure 2. We will see that annual inflation is a statistically significant determinant of conflict intensity; month-on-month inflation is not.

With the exception of a single outlier (rebel attacks in April 1986), the distribution of these transformed variables is approximately normal, and Table 2 shows their means, standard deviations and correlations. In the appendix we show that all of the variables are stationary. We will see that using the transformed data produces robust regression results. The implication of the logarithmic transformation in our model is that a given percentage change in one dimension of the conflict is associated with a certain percentage change in the others.

Similarly, we take logarithms of the aid variables discussed in the previous section. In the appendix we show that these variables are also stationary, except for narcotics aid. Nevertheless, the growth rate of narcotics aid is stationary. The four other variables used in our model are therefore as follows:

mil_t the logarithm of the deflated value of US military aid in the year including month t

oda_t the logarithm of the deflated value of total OECD overseas development assistance in the year including month t

gnc_t the growth rate of the deflated value of US counter-narcotics aid between the year including month t and the previous year

inf_t Consumer price inflation over the 12 months up to month t

Our model includes one further variable. We need to allow for the possibility that the major events of 1992 – the presidential coup in April and the capture of Guzmán in September – had an impact on the strategies of government and rebel forces. One way to capture the impact of specific events is to include a dummy variable equal to zero before the event and one afterwards. However, it does not make sense to include more than one such variable to capture the events of 1992, because the variables will be very highly correlated with each other. In the results reported below, we include a single dummy variable (cgz_t), switching from zero to one in the middle of 1992. Fortunately, changing the switching point to April or September makes no substantial difference to our results. The significance of a coefficient on such a dummy variable indicates that one or other of the events of 1992 had an impact on strategy, but the events are too close in time for there to be any power in a statistical test of which one is important.

4.2 Model structure and modeling techniques

Our model of conflict intensity is designed to shed light on the hypotheses listed in section 2.4. Now we restate these hypotheses in relation to the data we have presented.

$H1^R$. Rises in rbi and rbk will be associated with subsequent rises in pgi, pgk and civ.

$H2^R$. Rises in pgi, pgk and civ will be associated with subsequent reductions in rbi and rbk.

$H3^R$. Rises in mil will raise pgi, pgk, and civ.

$H4^R$. Rises in oda will reduce pgi, pgk, civ, rbi, and rbk.

$H5^R$. Rises in gnc will reduce pgi, pgk, civ, rbi, and rbk.

$H6^R$. Rises in inf will reduce pgi, pgk, and civ.

We explore these hypotheses by fitting a time-series model designed to capture the dynamics of the interactions of the different conflict intensity variables. There are several existing papers which use similar kinds of data, including studies of Algeria (Hagelstein, 2007), Colombia (Brauer *et al*., 2004; Restrepo and Spagat, 2010), Egypt (Fielding and Shortland, 2010) and Israel (Jaeger and Paserman, 2008). These papers exhibit a wide range of modelling techniques; a common obstacle in all of them is the lack of plausible identifying restrictions needed to establish the size of the instantaneous impact of one dimension of conflict (for example, the number of government attacks) on another (for example, the number of rebel attacks). One side in the conflict might respond within hours to activity by the other side. Therefore, if activity on both sides changes from one month to the next, we cannot tell how much of the change results from a government initiative and how much from a rebel initiative. Jaeger and Paserman (2008) address this problem by using very high frequency data. They use daily measures of conflict intensity, so the assumption that one side reacts to activity by the other side with a one-period lag is more plausible, and there is no need to identify instantaneous reactions. In conflicts subject to less intense media scrutiny than the Israeli-Palestinian conflict, finding reliable daily data is very difficult. As we have seen, some of the conflict data in Peru cannot be allocated with any certainty to a particular month, let alone a particular day. For this reason, we do not attempt to identify the magnitude of contemporaneous causal effects in the conflict variables. Instead, we explore the hypotheses listed above by using a form of impulse response analysis. This type of analysis, based on a reduced-form vector-autoregressive model (VAR), is discussed below. First, we describe the structure of the VAR that we use to model our conflict data.

Our VAR comprises the five conflict intensity variables, the four economic correlates of conflict intensity and the dummy variable for the events of 1992. Let $X_t = [pgi_t, pgk_t, civ_t, rbi_t, rbk_t]$ and $Z_t = [mil_t, oda_t, gnc_t, inf_t]$. These interactions between these variables are modeled as follows:

$$pgi_t = \alpha_{1t} + X_{t-1}\beta_{11} + X_{t-2}\beta_{12} + X_{t-3}\beta_{13} + X_{t-4}\beta_{14} + Z_t\theta_{11} + Z_{t-12}\theta_{12} + \delta_1.cgz_t + u_{1t} \qquad (1)$$

$$pgk_t = \alpha_{3t} + X_{t\text{-}1}\beta_{31} + X_{t\text{-}2}\beta_{32} + X_{t\text{-}3}\beta_{33} + X_{t\text{-}4}\beta_{34} + Z_t\theta_{31} + Z_{t\text{-}12}\theta_{32} + \delta_3.cgz_t + u_{3t} \quad (2)$$

$$civ_t = \alpha_{5t} + X_{t\text{-}1}\beta_{51} + X_{t\text{-}2}\beta_{52} + X_{t\text{-}3}\beta_{53} + X_{t\text{-}4}\beta_{54} + Z_t\theta_{51} + Z_{t\text{-}12}\theta_{52} + \delta_5.cgz_t + u_{5t} \quad (3)$$

$$rbi_t = \alpha_{2t} + X_{t\text{-}1}\beta_{21} + X_{t\text{-}2}\beta_{22} + X_{t\text{-}3}\beta_{23} + X_{t\text{-}4}\beta_{24} + Z_t\theta_{21} + Z_{t\text{-}22}\theta_{12} + \delta_2.cgz_t + u_{2t} \quad (4)$$

$$rbk_t = \alpha_{4t} + X_{t\text{-}1}\beta_{41} + X_{t\text{-}2}\beta_{42} + X_{t\text{-}3}\beta_{43} + X_{t\text{-}4}\beta_{44} + Z_t\theta_{41} + Z_{t\text{-}12}\theta_{42} + \delta_4.cgz_t + u_{4t} \quad (5)$$

Each β_{ij} term represents a (5 × 1) vector of parameters, and each θ_{ij} term a (4 × 1) vector of parameters. The u_{it} terms are regression residuals, and the α_{it} terms are intercepts specific to each month of the year. (We also allow for a different intercept in the *rbi* equation in April 1986, the month when there is an extreme outlier. However, excluding the *April 1986* dummy makes no substantial difference to our results.) Our model allows the current level of each conflict intensity variable to depend on levels of each of the other conflict intensity variables up to four months ago, and on the levels of the economic correlates of conflict intensity in the current and previous year.[8] The model can be viewed as a reduced-form representation of a system of structural equations in which each of the conflict variables has a contemporaneous effect on the others. The regression residuals u_i are linear combinations of the shocks to the structural equations, and therefore likely to be correlated with each other.

This model is not fitted to the whole twenty years of data depicted in Figure 1. Despite a number of casualties in isolated conflict events in 1980 and 1981, Stage II of SL's plan, the 'protracted people's war', began only in the later part of 1982 (Tapia, 1997). Similarly, the Peruvian government appears to have been genuine in its assessment of the organisation up until the end of 1982 as 'cattle rustlers' and 'bandits' (Fumerton, 2000). Recognition by both sides that they had engaged in a civil war appears to date from the end of 1982. We therefore model the conflict with data starting in January 1983. Dating the end of the conflict is less straightforward. Guzmán's capture in 1992 caused serious disruption to the operations of a very hierarchical rebel organisation, but the fighting continued. The introduction of the repentance law in early 1993 caused further disruption: over 5,000 rebels made use of this law up until its revocation at the end of 1994 (Palmer, 2007). This appears to have had a more substantial direct impact on rebel activity than Guzmán's capture, and Figure 1 shows a sharp drop in rebel attacks at the end of 1993. In the appendix, we explore the consequences for our results of changing the date at which our sample period ends. If we extend the sample period beyond the end of 1993, the parameters in the *rbi* and *rbk* equations

[8] Coefficients on lags of a higher order than this are not statistically significant.

become unstable. The results reported below are therefore based on fitting our model to data for January 1983 – December 1993.[9]

Including the seasonal intercepts, each regression equation in our model contains 41 parameters; these parameters are estimated on a sample of 132 observations. Many individual parameters are statistically insignificant, and the full unrestricted model represented by equations (1-5) is unlikely to be an accurate representation of the data generating process. For this reason, we fit both the unrestricted model and a restricted model in which the number of parameters is reduced using the algorithm discussed by Krolzig and Hendry (2001). This algorithm is designed to identify the most likely representation of the data generating process, assuming that the parameters of this process are some subset of the parameters of the unrestricted model. Most of the results presented below are based on the restricted model.

The parameters of our model can be estimated in a number of different ways. First, if we impose restrictions on equations (1-5), and if the residuals u_{it} are correlated with each other, then the Least Squares estimator (LS) is no longer efficient; alternatives include the Seemingly Unrelated Regressions estimator (SUR) and the Maximum Likelihood estimator (ML). Secondly, mil_t and gnc_t might not be independent of the conflict variables X_t: the size of the US military or counter-narcotics intervention in a particular year might depend on conflict intensity. One way of dealing with this problem is to use Greenbook data on US military or counter-narcotics aid to the whole of the rest of the world (or to the whole of Latin America) as an instrument for aid to Peru. Variations in global aid figures are unlikely to depend on the Peruvian conflict, and are likely to be correlated with the conflict only through the corresponding variations in aid to Peru.[10] The sample correlation coefficient for mil_t and the log of military aid to the rest of the world is 0.63; the equivalent correlation coefficient for gnc_t for is 0.58. If we use aid to Latin America instead of aid to the rest of the world, the correlation coefficients are 0.63 and 0.53 respectively. In other words, most of the variation in US aid to Peru is due to global changes in the US aid budget. Global figures are therefore likely to be a strong instrument for the Peruvian figures.[11]

[9] Equations (1-5) include lagged values of the conflict variables, so, the first observation in the data that we actually use is for September 1982.

[10] In the sample period, military aid to Peru constitutes 1% of worldwide military aid and 9% of Latin American military aid.

[11] Because we have only annual aid data, it is not feasible to include all of the regressors in equations (1-5) in the instrument set for aid: there is a high probability that such an approach would lead to spurious over-

With three choices of estimator (LS, SUR, ML) and three ways of dealing with the potential endogeneity of mil_t and gnc_t (ignoring it, using worldwide aid as an instrument, using Latin American aid as an instrument), we have nine different ways to fit our model. In the main text, we restrict our attention to the three alternatives using SUR. The other results are reported in the appendix; using one of the other estimators instead makes little difference to the results.

The parameters of the fitted model need to be interpreted with caution, because equations (1-5) represent a reduced-form system. Rather than trying to find some identifying restrictions with which to infer the parameters of the underlying structural model from the reduced-form parameters, we interpret our results by constructing impulse response profiles. Two types of impulse response profile are constructed. First, in order to interpret the β_{ij} parameters and address hypotheses H1-H2, we construct 'generalised impulse response' profiles (GIRs) for historically typical shocks, using the method of Evans and Wells (1983). GIRs are now common in time-series econometrics (Jacobs and Wallis, 2005), and the following paragraph provides a brief overview of the method.

Consider a system of $i = 1,\ldots, 5$ variables such as equations (1-5). There will probably be some correlation between the shocks u_i, so it does not make sense to plot out the response of the system to a single shock. Such an event – a change in u_1, for example, leaving the other u_i's unchanged – will never actually be observed. A GIR represents the response of the system to a more 'realistic' type of shock. *On average*, when u_1 changes, each other u_i is also changing by an amount indicated by the residual covariance matrix, $\Omega = \begin{bmatrix} \sigma_{11} & \cdots & \sigma_{51} \\ \vdots & \ddots & \vdots \\ \sigma_{15} & \cdots & \sigma_{55} \end{bmatrix}$. We can therefore think of a typical shock to the system that raises u_1 by an amount v as a vector of individual shocks $[u_1, u_2,\ldots, u_5]$ with magnitudes equal to $[v, (\sigma_{21}/\sigma_{11}) \cdot v,\ldots, (\sigma_{51}/\sigma_{11}) \cdot v]$. Using the estimated β_{ij} parameters, we can trace out the effect of this shock on each variable in the system over subsequent months. This shows us what happens *on average* after a v-shock to *pgi*, which also involves unanticipated contemporaneous shocks to the rest of the system. The same method can be used to characterize the response of the system to a typical v-shock in any of the u_i using magnitudes equal to $[(\sigma_{1i}/\sigma_{ii}) \cdot v,\ldots, v,\ldots, (\sigma_{5i}/\sigma_{ii}) \cdot v]$.

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fitting of the aid equation. We use *only* the global aid variable as an instrument for aid to Peru, so our approach is different from the traditional Instrumental Variables estimator.

We use a different type of response profile to interpret the estimated θ_{ij} parameters and address hypotheses H3-H6, because these parameters capture the impact on the system of exogenous changes in the different aid variables, and in inflation. For example, let the vector θ_{ij} = [θ_{ij}^1 θ_{ij}^2 θ_{ij}^3 θ_{ij}^4]′.[12] If the variable *mil* increases by an amount *w*, then the immediate effect on *pgi* is a change of magnitude $w \cdot \theta_{11}^1$, the immediate effect on *pgk* is a change of magnitude $w \cdot \theta_{21}^1$, and so on. In the next month, these changes in conflict intensity will be magnified through the interactions between the different conflict variables captured by the β_{i1} parameters. The response of the system in subsequent months can then be traced out using the other β_{ij} parameters, and, if the hypothetical increase in *mil* persists into the next year, using the θ_{i2} parameters. The same can be done for hypothetical increases in *oda*, *gnc* and *inf*.

4.3 Results[13]

Table 3 reports the parameters of the restricted model estimated by SUR, along with corresponding t-ratios. (LS and ML estimates are presented in the appendix, as are the parameters of the unrestricted model.) Column 1 in the table corresponds to the estimates in which no instruments are used for *mil* or *gnc*; column 2 corresponds to the estimates using worldwide aid figures as instruments, and column 3 to the estimates using Latin American aid figures as instruments. Generally, the use of instruments makes little difference to the results, except that the coefficients on gnc_t (but not $gnc_{t\text{-}12}$) in the *pgk* equation and on cgz_t in the *rbk* equation become statistically insignificant. Table 4 presents descriptive and diagnostic statistics for both the unrestricted model and the Table 3 (Column 1) model, showing that there is no evidence of heteroskedasticity or residual autocorrelation, that the regression residuals are approximately normally distributed, and that the model parameters are constant over the sample period.

Table 5 reports the residual correlation coefficients. All of these coefficients are positive, and some are significantly greater than zero. This suggests that the parameters in Table 3 should be interpreted as reduced-form parameters, and we interpret them using impulse response profiles. These profiles are shown in Figures 4-12, and represent the response of the system over the 24 months following a typical shock to one of the conflict variables (the shock lasting for a single month), or following an increase in one of the aid

[12] In the restricted version of the model, some of the individual θ_{ij}^k parameters may be equal to zero.

[13] The results in this section were produced using *TSP 5.0, GiveWin 2.0* and *PCGets 1.0*.

variables, or in inflation (the increase lasting for two years). The black lines indicate the estimated responses in months 1-24 following the shock in month zero, and the gray lines indicate points two standard errors above and below these estimates. In addition to the response profiles for increases in aid and inflation in Figures 9-12, Table 6 reports estimates of the impact of such increases in the steady state, were they to be permanent. The hypothetical shocks are of magnitude $v = 1$, and the hypothetical increases in aid or inflation are of magnitude $w = 1$; we will interpret the figures by referring to the effect of a 1% shock to a conflict variable, or of a 1% increase in aid or inflation. Figures 4-12 are based on the coefficients in Table 3 (column 1); figures based on one of the other sets of coefficients in Table 3 or in the appendix are very similar. We plot the responses of all of the conflict variables to all of the shocks, but our discussion focuses on the subset of responses relevant to our hypotheses.

Figures 7-8, plotting responses to typical shocks to *rbi* and *rbk*, are relevant to hypothesis H1. It can be seen that *pgi*, *pgk* and *civ* all rise following such shocks. The responses of *pgi* and *pgk* following a shock to *rbi* (Figure 7), and of *pgk* following a shock to *rbk* (Figure 8), are all more than two standard errors above zero in months 4-5, indicating that these are statistically significant effects. In these months, the estimated size of the response of *pgi* to the *rbi* shock and of *pgk* to the *rbk* shock is about 0.25: a typical shock raising *rbi* (or *rbk*) by 1% leads to a subsequent increase in *pgi* (or *pgk*) of about 0.25%. The magnitude of the response of *pgk* to a typical shock to *rbi* is about three times as large. This is evidence for hypothesis H1: unanticipated increases in the overall rebel conflict effort, and in the extent of rebel abuse of civilians, are followed by corresponding (although less than proportionate) increases in the government conflict effort and in government abuse, as measured by *pgi* and *pgk*. The response of *civ* to typical shocks to *rbi* and *rbk* is positive but not significantly greater than zero, so we do not have any strong evidence that the number of disappearances increases following an unanticipated surge in rebel activity.

Figures 4-6, plotting responses to typical shocks to *pgi*, *pgk* and *civ*, are relevant to hypothesis H2. A typical shock to any of these variables is associated with a subsequent increase in *rbi* and *rbk*. In all cases, the increase is significantly greater than zero at some point during the first four months following the shock. A typical shock raising *pgi* by 1% leads to a subsequent increase in *rbi* by about 0.2% and in *rbk* by about 0.3% within the next three to four months (Figure 4). For a typical shock to *pgk* (Figure 6) or *civ* (Figure 8), the responses of *rbi* and *rbk* are much smaller, with the impulse response profiles peaking below 0.1. That is, rebel activity responds more to a shock raising the level of overall government military effort than it does to a shock raising the level of government abuse of civilians. Nevertheless, all of the effects are statistically significant. These results imply a definitive rejection of hypothesis H2. Increases in government activity are certainly not followed by a reduction in rebel activity. There is a cycle of violence in which increased civilian abuse by either side is followed by increased civilian abuse by the other; the same is true of the two sides' overall level of military effort.

Figure 9, plotting the responses of the conflict intensity variables to an increase in the level of US military aid to the Peruvian government, is relevant to hypothesis H3. Note that this figure plots the response of the conflict to a sustained increase in the level of aid, not to a temporary shock, so the response profiles do not converge back to zero. All of the responses are positive, indicating that an increase in military aid will raise all dimensions of conflict intensity. For *pgk* (but not for *pgi* or *civ*), the responses are significantly greater than zero, providing some evidence for hypothesis H3: more military aid raises the level of government abuse of civilians. Note also that there are significant positive responses in *rbi* and *rbk*. In Table 6, we see that the eventual effect of a sustained increase in the level of military aid by 1% would be to raise *pgk* by 0.07%, *rbi* by 0.11% and *rbk* by 0.05%. It is striking that the effect on *rbi* is greater than the effect on *pgi* (which is not significantly greater than zero). These effects are estimated in a reduced-form model, so we cannot be sure of the reason for this,[14] but it might be because military aid changes the way in which government forces fight (for example, they might fight more effectively or more murderously), and this induces a response in rebel mobilization.

Figure 10, plotting the responses of the conflict intensity variables to an increase in the level of overseas development assistance, is relevant to hypothesis H4. All of the responses are negative, indicating that an increase in overseas development assistance will lower all dimensions of conflict intensity. Again, it is the responses of *pgk*, *rbi* and *rbk* that are statistically significant. In Table 6, we see that the eventual effect of a sustained increase in the level of overseas development assistance by 1% would be to lower *pgk* by 0.89%, *rbi* by 1.36% and *rbk* by 0.61%. These effects provide strong evidence for hypothesis H4: when we control for military aid levels, we see that general aid has a large beneficial effect on the Peruvian conflict.

[14] In particular, we cannot infer anything from the size or significance level of any one individual θ_{ij}^{1} coefficient in equations (1-5), because this coefficient is likely to be a linear combination of the effects of *mil* on different conflict variables in the underlying structural model.

A similar pattern emerges in Figure 11, which addresses hypothesis H5 by plotting the responses of the conflict intensity variables to an increase in the rate of growth of counter-narcotics aid. All five response profiles in the figure are significantly below zero. The largest effects are in the variables measuring government abuse of civilians, *pgk* and *civ*. In Table 6, we see that the eventual effect of a sustained increase in the rate of growth of counter-narcotics aid by 1% would be to lower *pgi* by 1.37%, *pgk* by 1.94%, *civ* by 1.81%, *rbi* by 0.36% and *rbk* by 0.62%. These are the largest beneficial effects in the model, and they constitute strong evidence for hypothesis H5. However, they should be interpreted with caution, because it is unrealistic to suppose that a higher rate of growth of counter-narcotics aid could be sustained for ever. The model suggests that counter-narcotics aid does have a large impact on conflict intensity, but, given the time-series properties of the aid series, the impact has been short-lived.

Figure 12 addresses our final hypothesis by plotting the responses of the conflict intensity variables to an increase in the rate of inflation. In this case, the evidence is mixed. The response of *pgi* is statistically insignificant. For *pgk* there is a significant negative response, and for *civ* there is a significant positive response. A 1% increase in inflation reduces *pgk* by about 0.2% and increase *civ* by about 0.1%. Given the tripe-digit levels of inflation observed within the sample period, these are large effects. With a sustained reduction in the inflation rate the *pgk* response persists, but the *civ* response declines slowly, and is insignificantly different from zero in the steady state. One interpretation of these effects is that an increase in inflation makes it more difficult to run the military operations required to terrorize the civilian population effectively (especially when these operations involve paramilitaries), and the government then turns to the detention of civilians as a low-cost alternative. Overall, there is no clear evidence for hypothesis H6.

5. Summary and Conclusion

Ball *et al*. (2003) estimate that between 1980 and 2000, some 69,280 civilians died at the hands of government or rebel forces in Peru. Nearly half of these deaths were in the Ayacucho region, where the fatality rate was over 5%. Previous studies of civil wars in Peru and elsewhere have used cross-sectional data to analyze those characteristics of civilians and soldiers (and of the areas where they live) that are associated with a high risk of civilian abuse. In this paper we have analyzed a different dimension of the data, looking at the factors that led to changes in the level of abuse in Peru while the war was ongoing.

Our first main finding is that when one side in the war increased its level of civilian abuse or overall military effort, the other side responded in kind. There was a cycle of violence in which each side responded in the same way to activity by the other side. This makes the war in Peru different from some other conflicts in which there are marked asymmetries in strategy, for example, the Israeli-Palestinian conflict (Jaeger and Paserman, 2008). In wars like the one in Peru, encouraging or facilitating an increase in the government forces' level of military effort in the field will only exacerbate the level of conflict and entail higher civilian casualties. The war in Peru was brought to an end not by the defeat of rebel forces in the field, but by the arrest of the rebel leader outside the theater of battle, and the subsequent amnesty offered to his lieutenants.

This leads to our second main finding: military aid to the Peruvian government led directly to an increase in the level of conflict intensity and the amount of civilian suffering. By contrast, both general overseas development assistance and specific counter-narcotics aid led directly to a decrease the level of conflict intensity and the amount of civilian suffering. Military aid raised the fighting the capacity of one side in the cycle of violence, but other types of aid increased the opportunity cost of fighting for one side or another. The Peruvian data provides evidence that participants in this civil war do respond to economic incentives. Through economic interventions, the international community has the capacity both to mitigate civil conflict and to exacerbate it: in Peru it did both.

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Table 1: Totals of the Conflict Intensity Variables (January 1980 – December 2000)

	government / paramilitary attacks	civilian casualties in government / paramilitary attacks	civilian detentions	rebel attacks	civilian casualties in rebel attacks
total of monthly observations	3328	5089	5795	3704	7243
total of annual observations	849	820	735	193	1133
annual observations as a fraction of all observations	0.20	0.14	0.11	0.05	0.14

Table 2: Descriptive Statistics for the transformed Conflict Intensity Variables

(January 1983 – December 1993)

(i) Means and Standard Deviations

	pgi	*pgk*	*civ*	*rbi*	*rbk*
mean	3.150	3.276	3.342	3.170	3.794
std. dev.	0.565	0.948	0.983	0.440	0.738

(ii) Correlations

	pgi	*pgk*	*civ*	*rbi*
pgk	0.551			
civ	0.754	0.319		
rbi	0.509	0.370	0.423	
rbk	0.414	0.288	0.395	0.760

Table 3: SUR Regression Coefficients

	(1) no instruments for *mil* / *gnc*		(2) world instruments for *mil* / *gnc*		(3) Latin American instruments for *mil* / *gnc*	
<u>*pgi* equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-1}	0.399	*6.48*	0.411	*6.62*	0.399	*6.46*
pgi_{t-3}	0.335	*3.68*	0.354	*3.87*	0.337	*3.71*
civ_{t-3}	-0.129	*-2.79*	-0.142	*-3.03*	-0.135	*-2.95*
rbk_{t-1}	0.124	*2.80*	0.118	*2.66*	0.129	*2.96*
rbk_{t-3}	0.112	*2.40*	0.116	*2.49*	0.124	*2.68*
gnc_{t}	-0.202	*-2.41*	-0.295	*-2.30*	-0.371	*-2.61*
gnc_{t-12}	-0.246	*-3.13*	-0.163	*-2.28*	-0.176	*-2.48*
σ	0.33		0.30		0.26	
<u>*pgk* equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-1}	0.462	*2.63*	0.519	*2.92*	0.522	*2.92*
pgi_{t-3}	0.711	*3.04*	0.725	*3.04*	0.723	*3.02*
pgk_{t-4}	-0.249	*-3.04*	-0.245	*-2.95*	-0.249	*-2.97*
civ_{t-3}	-0.373	*-3.59*	-0.363	*-3.39*	-0.352	*-3.31*
rbi_{t-4}	0.555	*2.72*	0.504	*2.44*	0.489	*2.33*
rbk_{t-2}	0.224	*2.13*	0.232	*2.17*	0.243	*2.26*
gnc_{t}	-0.477	*-2.48*	-0.296	*-1.02*	-0.166	*-0.45*
gnc_{t-12}	-0.685	*-3.63*	-0.468	*-2.76*	-0.467	*-2.69*
inf_{t}	-0.183	*-3.25*	-0.193	*-3.35*	-0.188	*-3.12*
cgz_{t}	-0.953	*-4.59*	-0.919	*-4.28*	-0.903	*-3.74*
σ	0.72		0.35		0.73	
<u>*civ* equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-3}	0.734	*3.76*	0.762	*3.99*	0.706	*3.37*
civ_{t-3}	-0.298	*-2.70*	-0.337	*-3.09*	-0.299	*-2.87*
rbk_{t-1}	0.245	*2.34*	0.232	*2.26*	0.265	*2.01*
rbk_{t-3}	0.287	*2.61*	0.311	*2.88*	0.320	*2.52*
gnc_{t}	-0.482	*-2.48*	-1.040	*-3.40*	-0.925	*-2.89*
gnc_{t-12}	-0.538	*-2.98*	-0.334	*-2.08*	-0.381	*-2.37*
inf_{t}	0.107	*2.43*	0.099	*2.29*	0.093	*3.02*
σ	0.76		0.48		0.76	
<u>*rbi* equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-4}	0.152	*3.00*	0.129	*2.41*	0.135	*2.56*
rbi_{t-1}	0.194	*2.90*	0.279	*4.14*	0.255	*3.80*
rbi_{t-3}	0.233	*3.58*	0.263	*3.83*	0.238	*3.47*
mil_{t}	0.059	*3.90*	0.027	*1.51*	0.045	*2.31*
oda_{t}	-0.726	*-4.60*	-0.439	*-3.00*	-0.449	*-3.12*
April 1986	-1.052	*-4.02*	-0.992	*-3.56*	-1.046	*-3.80*
σ	0.30		0.11		0.37	
<u>*rbk* equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-2}	0.163	*1.12*	0.162	*1.10*	0.156	*0.88*
pgi_{t-3}	0.353	*2.02*	0.368	*2.08*	0.368	*2.96*
civ_{t-3}	-0.117	*-1.48*	-0.128	*-1.61*	-0.130	*-1.79*
rbi_{t-2}	0.364	*2.37*	0.355	*2.29*	0.362	*2.37*
cgz_{t}	-0.411	*-2.51*	-0.256	*-1.60*	-0.290	*-1.23*
σ	0.67		0.70		0.68	

Table 4: Regression Diagnostic and Descriptive Statistics

The restricted model is estimated by SUR, with no instruments for mil or gnc.

	pgi equation	*pgk* equation	*civ* equation	*rbi* equation	*rbk* equation
unrestricted model diagnostic statistic p-values					
Chow F-Test§	0.65	0.94	0.93	0.17	0.50
Jarque-Bera χ^2-Test	0.63	0.70	0.77	0.38	0.59
LM autocorrelation F-test	0.76	0.13	0.74	0.86	0.51
Heteroscedasticity F-test	1.00	0.97	0.86	0.99	0.99
unrestricted model descriptive statistics					
R^2	0.78	0.59	0.56	0.70	0.41
Akaike Criterion	-2.06	-0.39	-0.26	-2.25	-0.54
restricted model diagnostic statistic p-values					
Chow F-Test§	0.98	0.90	0.93	0.62	0.89
Jarque-Bera χ^2-Test	0.25	0.93	0.67	0.25	0.02
LM autocorrelation F-test	0.28	0.25	0.41	0.76	0.47
Heteroscedasticity F-test	0.07	0.75	0.11	0.98	0.40
restricted model descriptive statistics					
R^2	0.71	0.51	0.48	0.62	0.31
Akaike Criterion	-2.09	-0.48	-0.41	-2.35	-0.72

§ The null for the Chow Test is that the estimated parameters using the first half of the sample (66 observations) are equal to the estimated parameters using the second half of the sample.

Table 5: Regression Residual Correlation Coefficients

The restricted model is estimated by SUR, with no instruments for US intervention.

	pgi	*pgk*	*civ*	*rbi*
pgk	0.261			
civ	0.560	0.018		
rbi	0.243	0.149	0.103	
rbk	0.162	0.049	0.210	0.624

Table 6: Steady-State Coefficients

These coefficients are based on the SUR estimates, with no instruments for US intervention.

	pgi equation		*pgk* equation		*civ* equation		*rbi* equation		*rbk* equation	
	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
mil	0.027	*1.554*	0.072	*2.463*	0.036	*1.666*	0.110	*3.877*	0.050	*1.916*
oda	-0.333	*-1.568*	-0.894	*-2.564*	-0.440	*-1.682*	-1.357	*-4.406*	-0.614	*-1.934*
gnc	-1.365	*-2.688*	-1.944	*-3.362*	-1.814	*-3.366*	-0.362	*-1.979*	-0.624	*-1.874*
inf	-0.051	*-1.703*	-0.218	*-3.648*	0.039	*1.377*	-0.013	*-1.456*	-0.036	*-1.580*
cgz	-0.296	*-1.754*	-1.058	*-4.352*	-0.391	*-1.904*	-0.079	*-1.520*	-0.546	*-2.262*

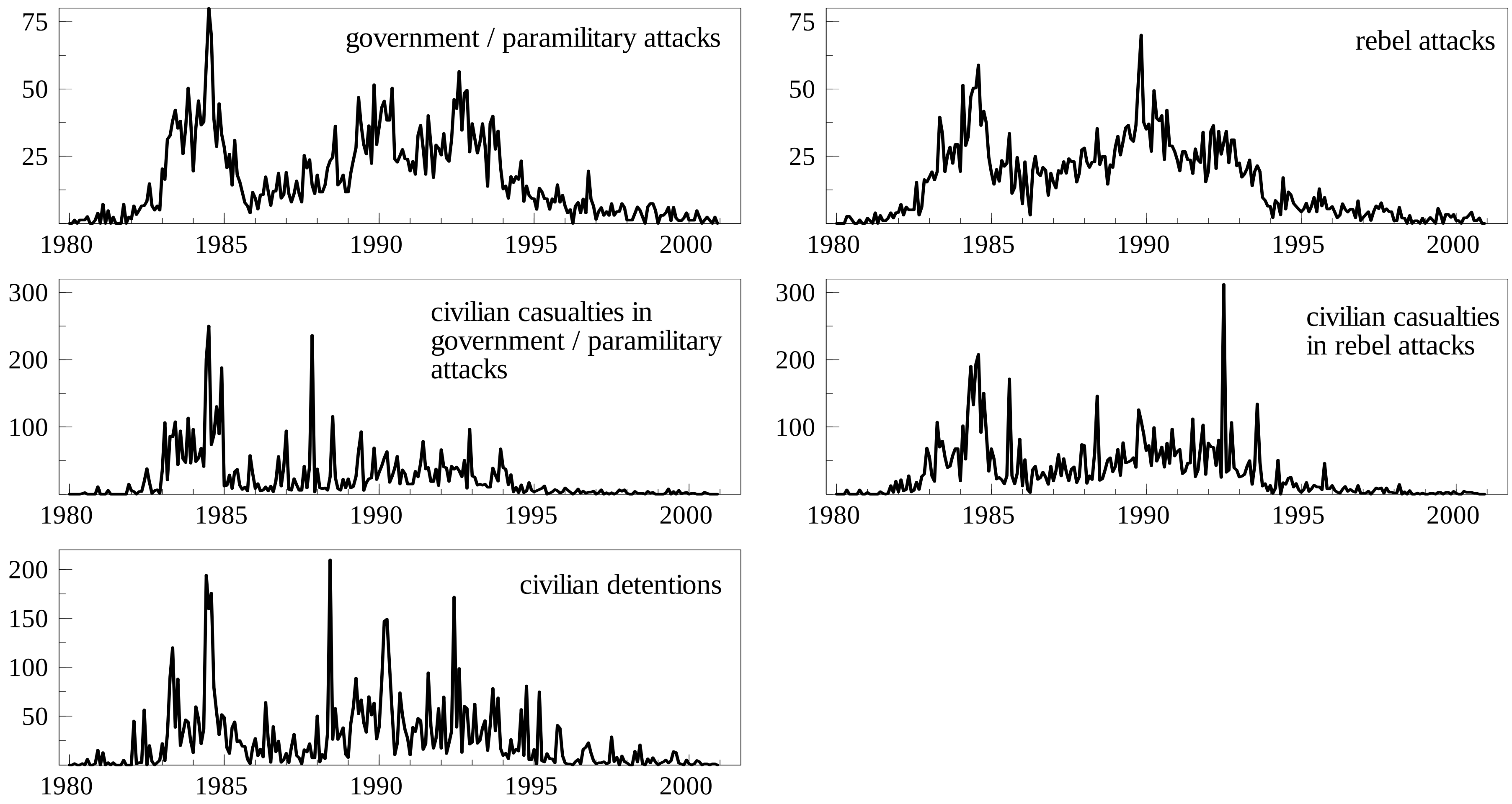

Figure 1: The Monthly Conflict Series (Including Interpolated Annual Totals)

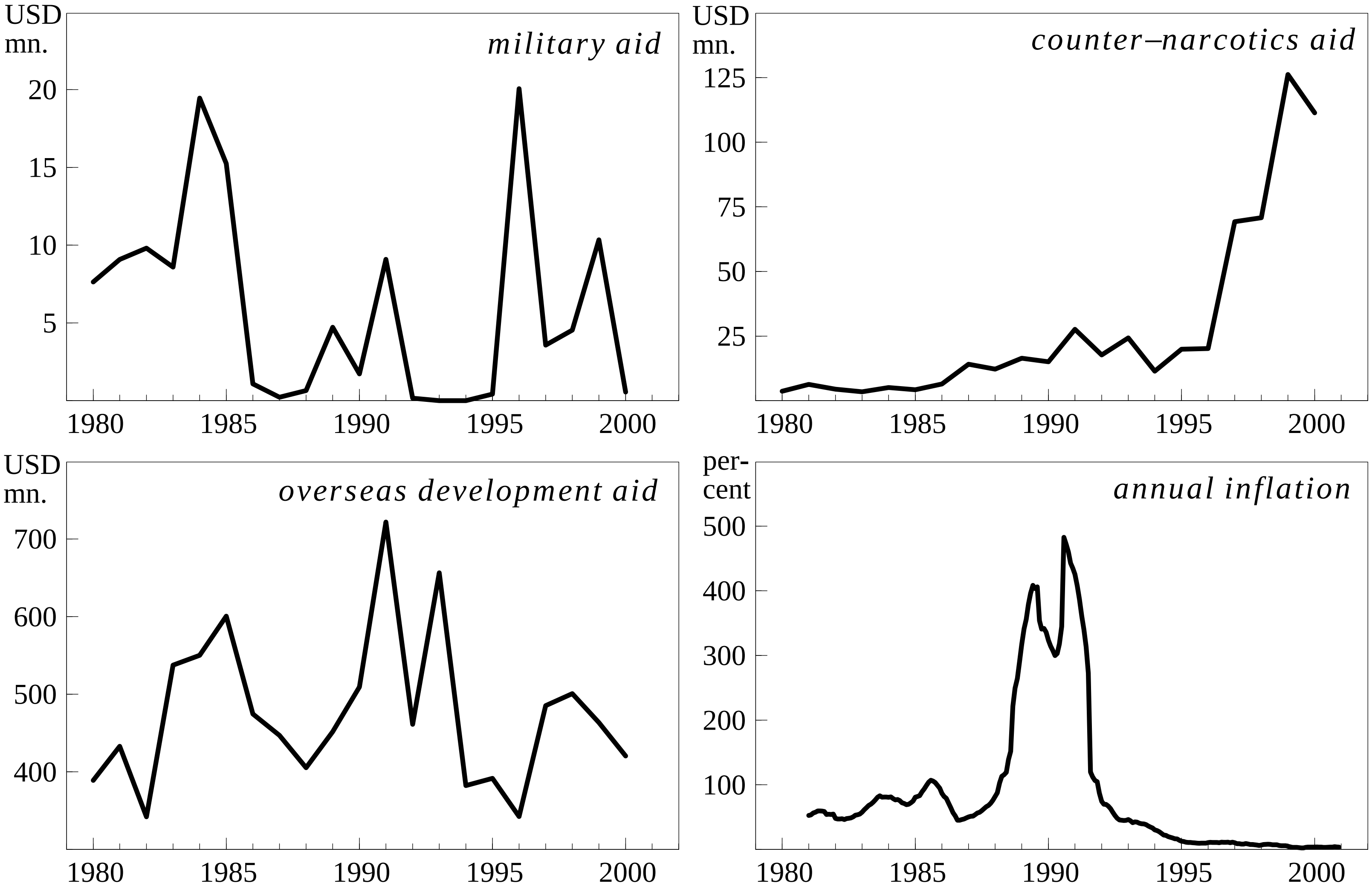

Figure 2: The Correlates of Conflict Intensity

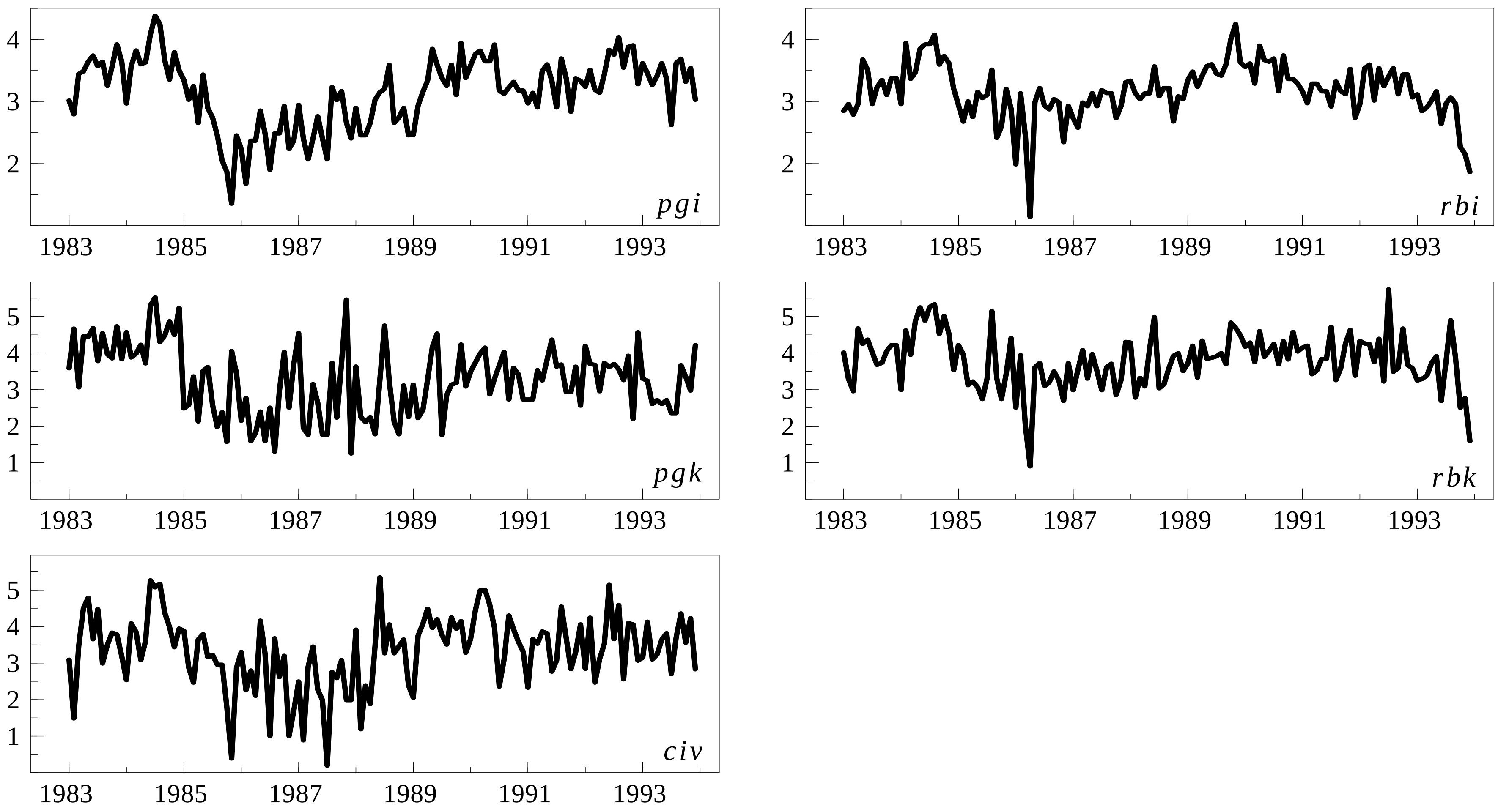

Figure 3: The Transformed Monthly Conflict Series

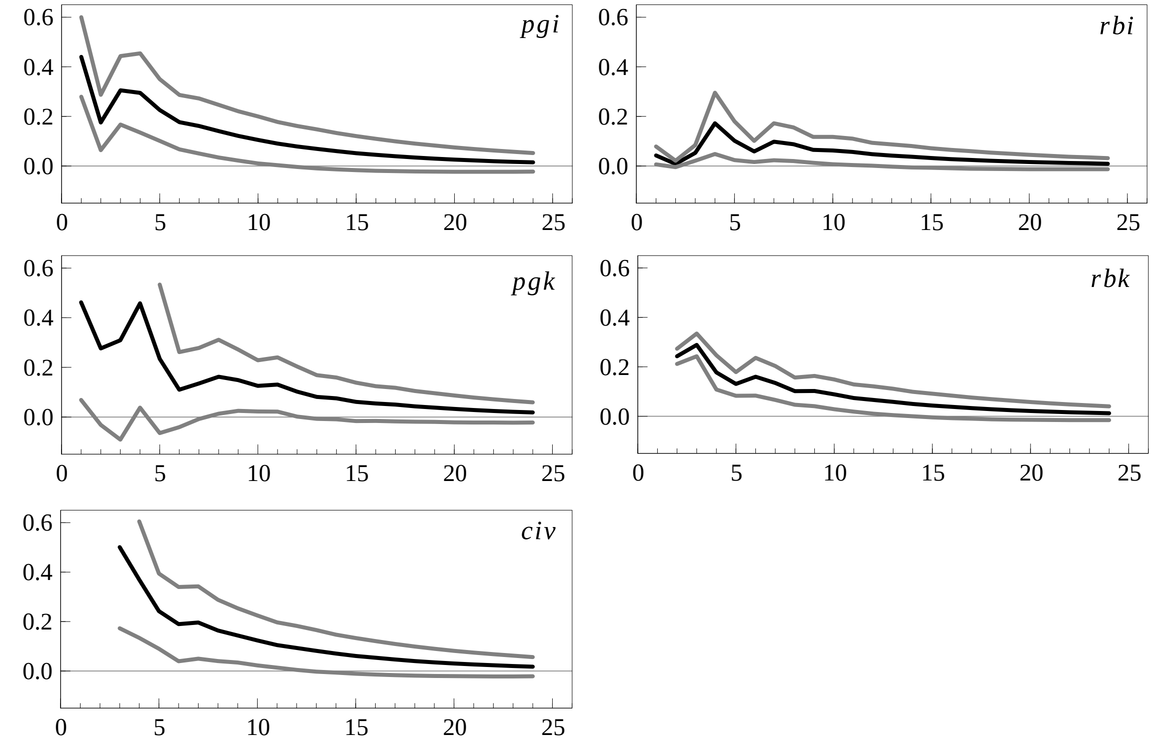

Figure 4: Generalized Impulse Responses for a Unit Shock to *pgi*

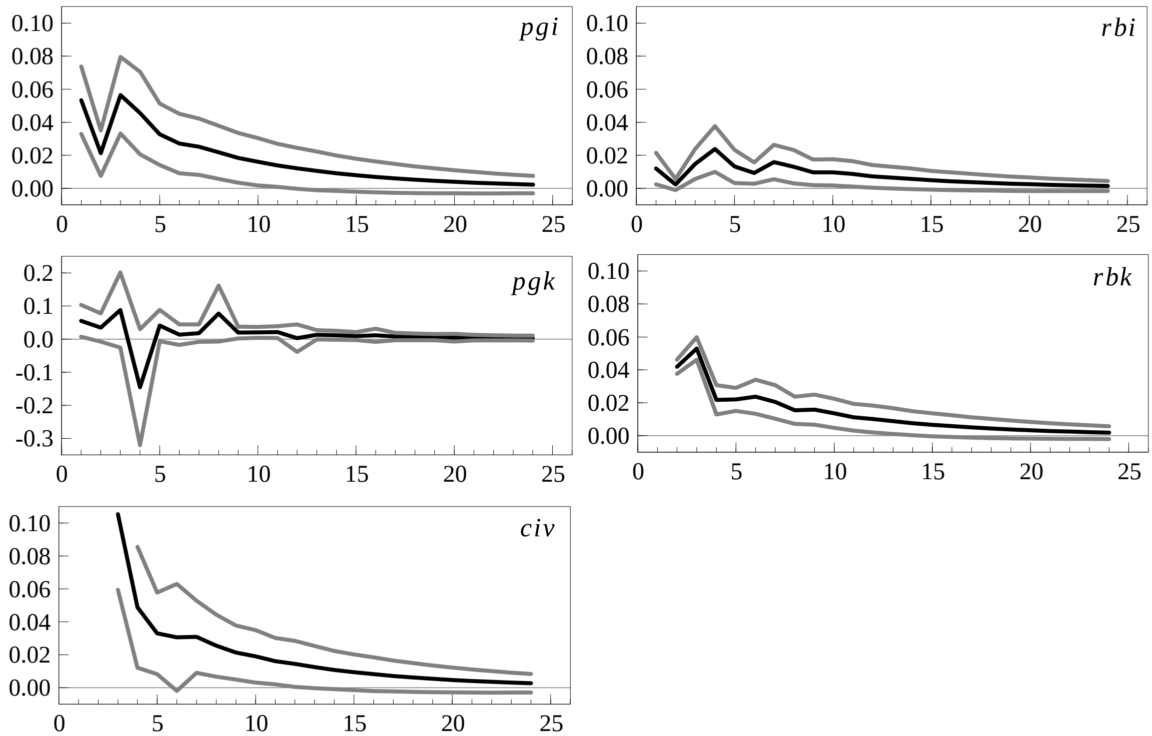

Figure 5: Generalized Impulse Responses for a Unit Shock to *pgk*

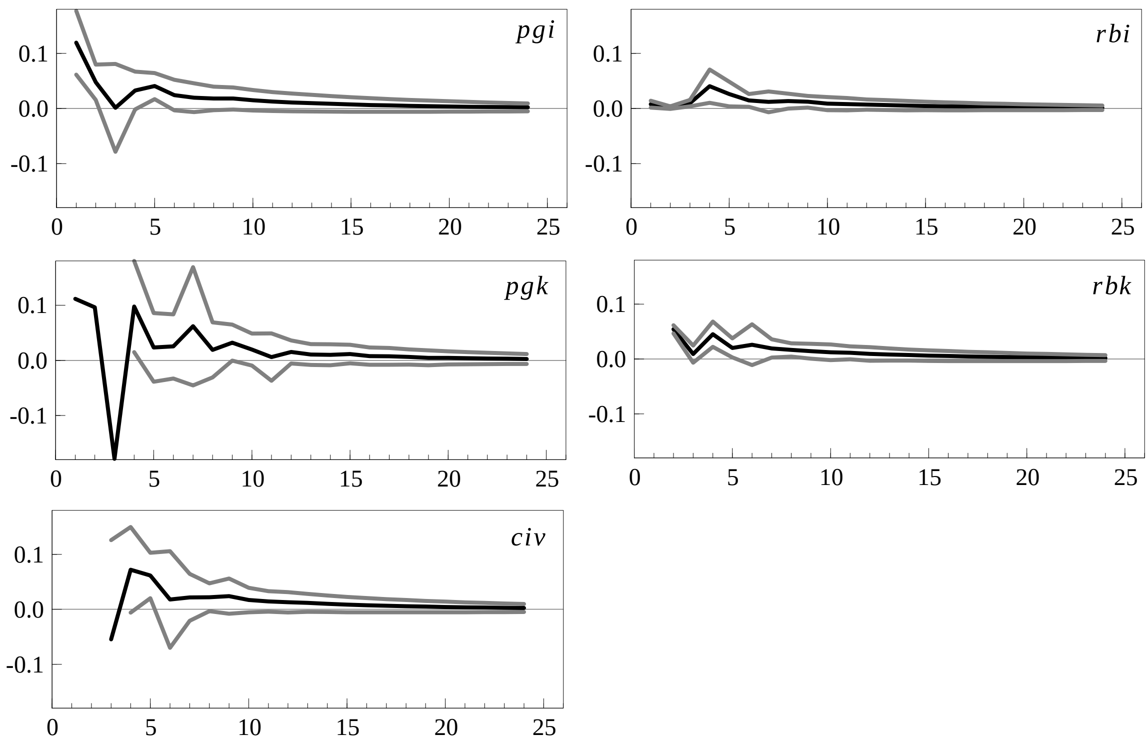

Figure 6: Generalized Impulse Responses for a Unit Shock to *civ*

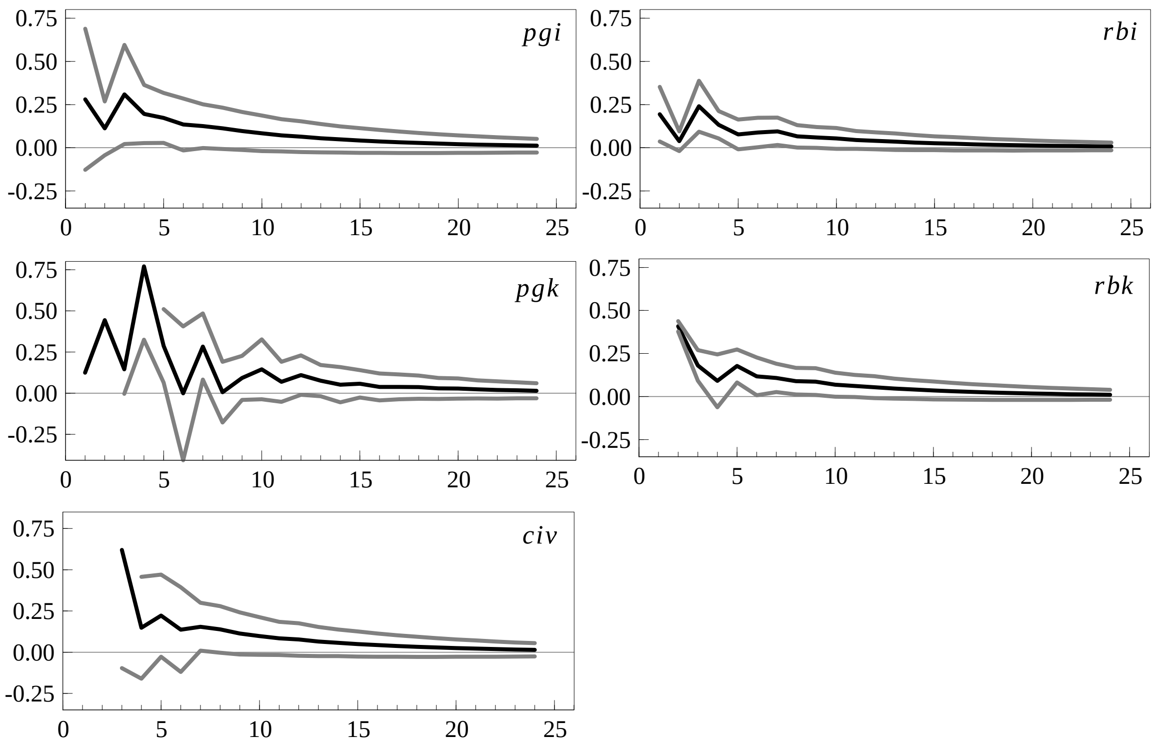

Figure 7: Generalized Impulse Responses for a Unit Shock to *rbi*

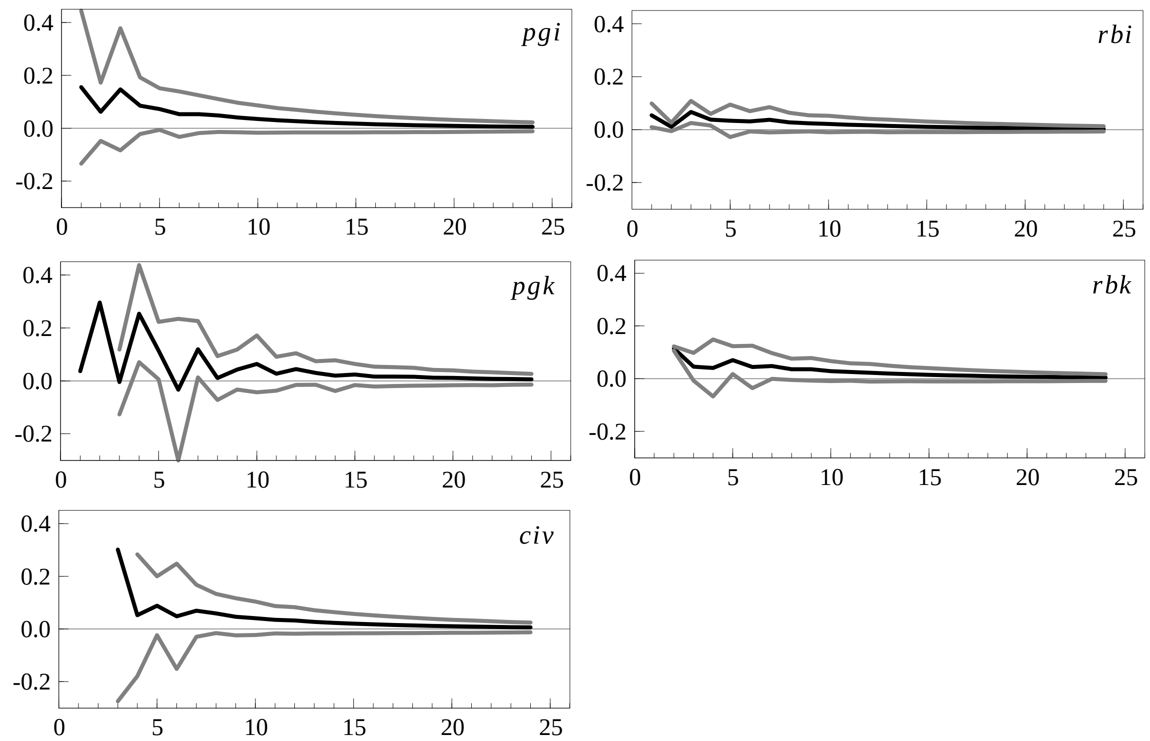

Figure 8: Generalized Impulse Responses for a Unit Shock to *rbk*

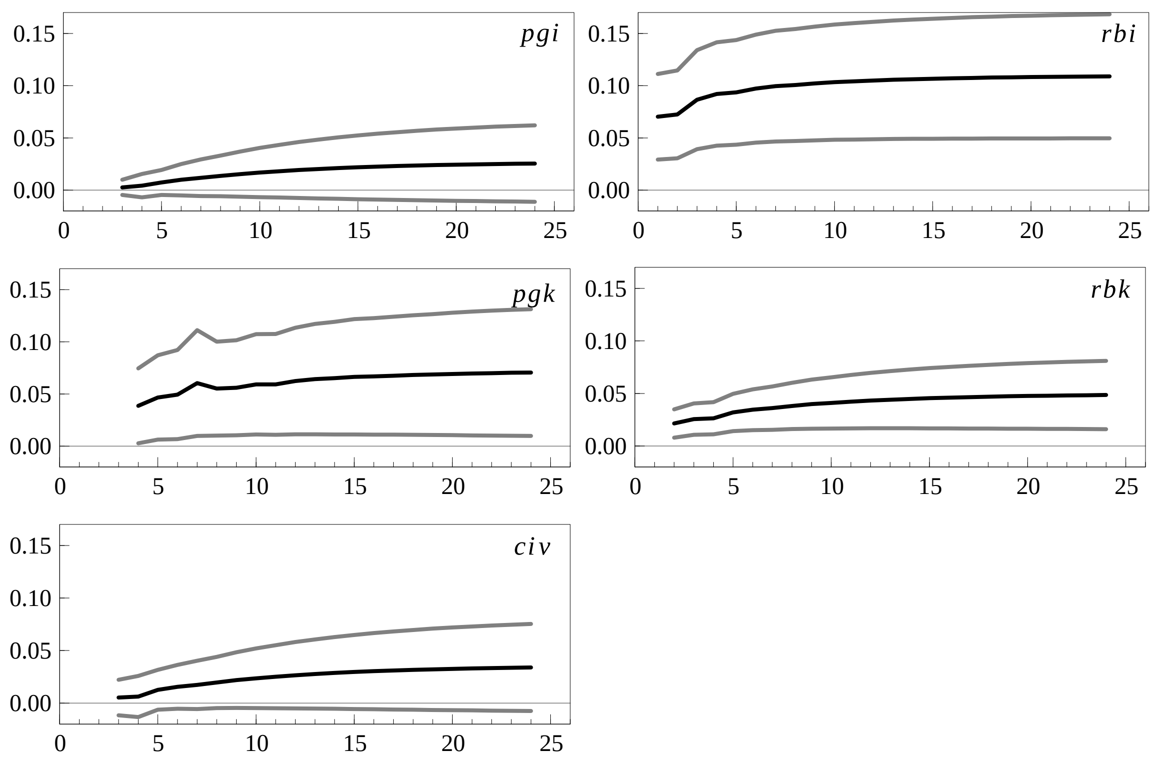

Figure 9: Responses to a Unit Increase in *mil*

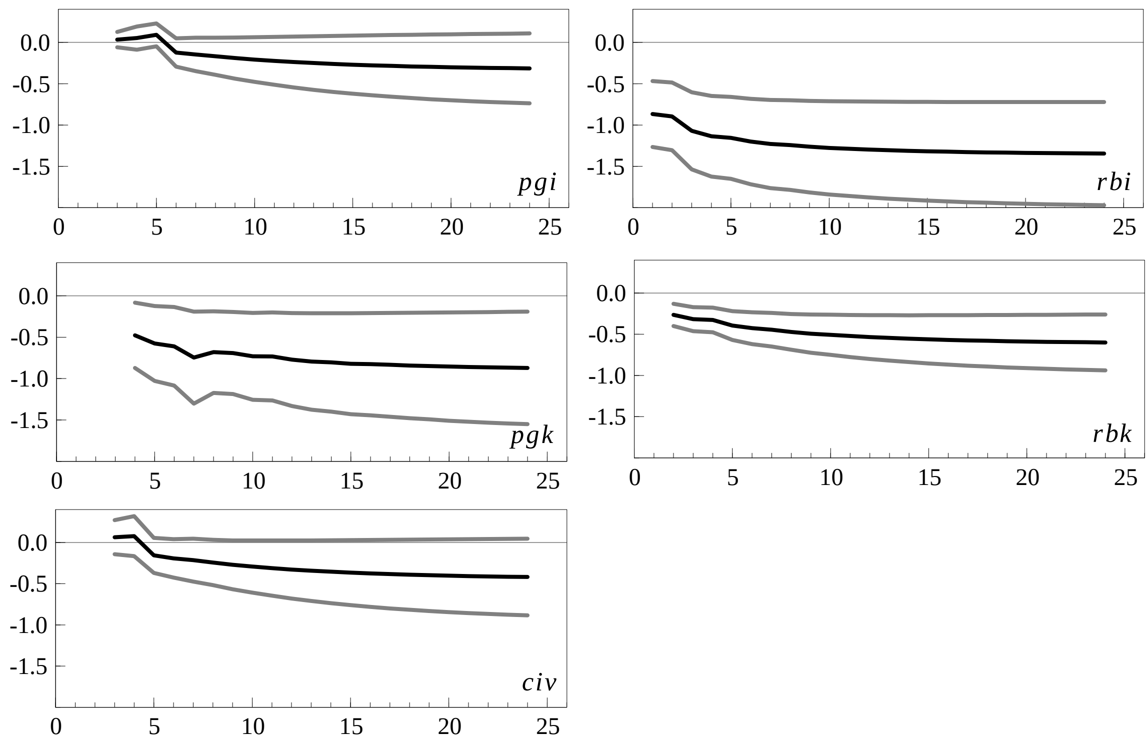

Figure 10: Responses to a Unit Increase in *oda*

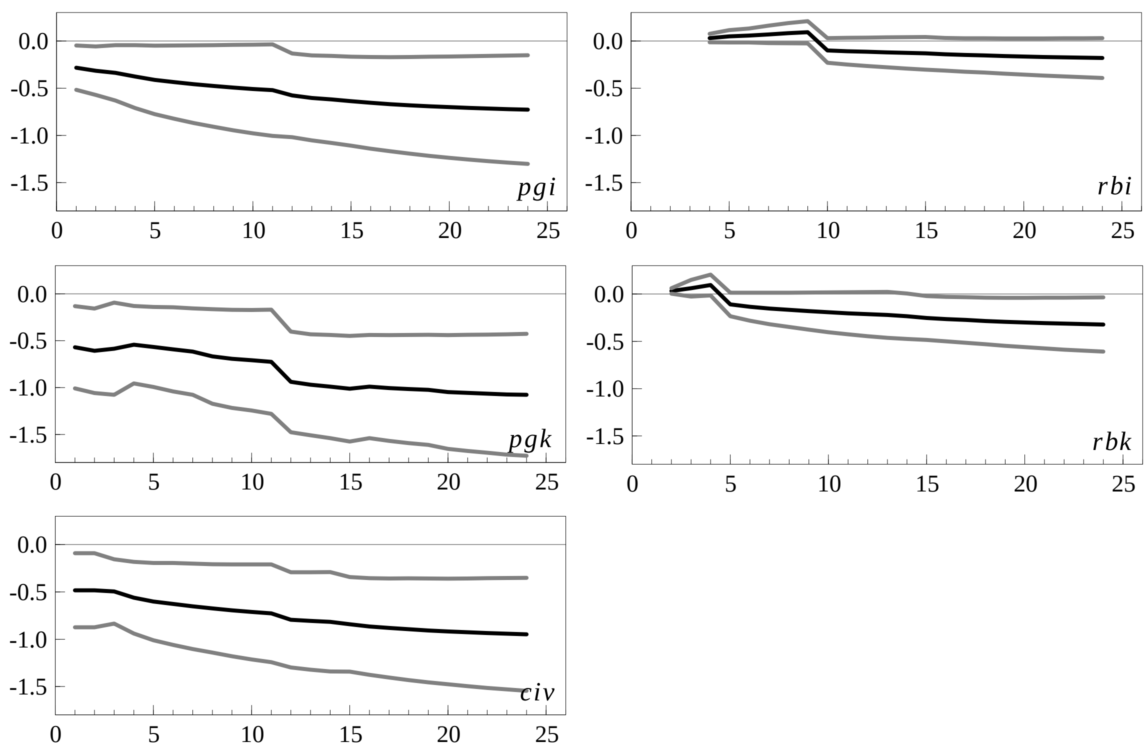

Figure 11: Responses to a Unit Increase in *gnc*

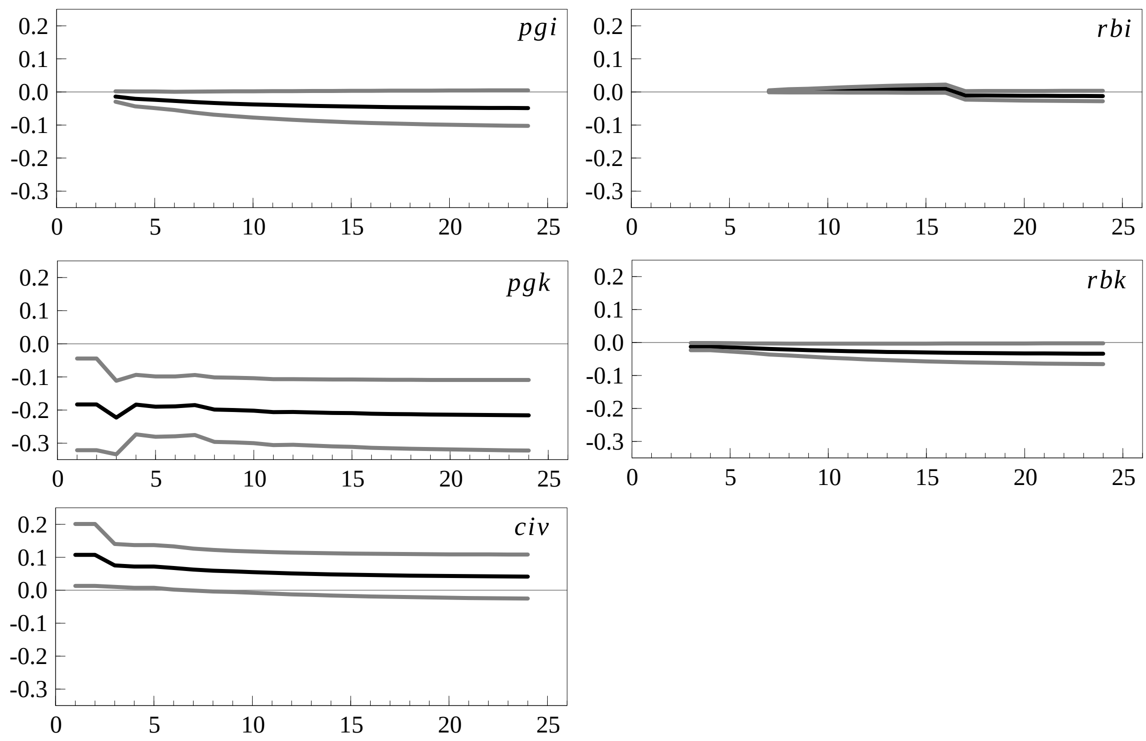

Figure 12: Responses to a Unit Increase in *inf*

APPENDIX

A1. Tests for the Stationarity of the Variables in the Model

Table A1 reports Augmented Dickey-Fuller test statistics for the variables of interest. Part (i) of the table deals with the variables that are observed monthly: the conflict variables and inflation.[A1] Part (ii) of the table deals with the aid variables, which are observed annually. In part (i), the regression equation applied to each variable z_t is:

$$\Delta z_t = \gamma_t + \Sigma_k [\eta_k \cdot \Delta z_{t-k}] + \lambda \cdot z_{t-1} + \varepsilon_t \qquad \text{(A1)}$$

where γ_t is a seasonal intercept, ε_t a regression residual, and $k = 1,\ldots, K$. The lag order K is chosen on the basis of the Akaike Information Criterion. In the case of rbi_t, a dummy variable for April 1986 is also included. The table notes the sample used for estimation (which is the same as in Table 3 of the main text), the value of K, and the t-ratio on λ. With all of the conflict variables, λ is less than zero, and the t-ratio is significant at the 5% level. The null that x_t is difference-stationary can therefore be rejected in favour of the alternative that it is stationary in levels. With inflation λ is less than zero, and the t-ratio is significant at the 10% level.

The regression equation which provides the results in part (ii) of the table is:

$$\Delta z_t = \gamma + \Sigma_k [\eta_k \cdot \Delta z_{t-k}] + \lambda \cdot z_{t-1} + \varepsilon_t \qquad \text{(A2)}$$

where γ is a constant term. In this case, the sample spans a larger period than in part (i), because with annual data a test based on such a short sample would have very little power. With the annual data we use as large a sample as is available in our data sources, and the sample size varies slightly from one variable to another. The four variables appearing in part (ii) of the table are mil_t, oda_t, gnc_t, and the log of the level of counter-narcotics aid, nc_t.[A2] With mil_t the t-ratio on λ is significant at the 10% level, and with oda_t it is significant at the 1% level. With nc_t the t-ratio on λ is not statistically significant, so the null that nc_t is difference-stationary cannot be rejected. However, with gnc_t the t-ratio on λ is significant at the 1% level.

[A1] Let p_t stand for the logarithm of the price index. The measure of annual inflation used in the main text (inf_t) is defined as $\Delta_{12}\, p_t$. This is a moving average process, so a standard Augmented Dickey-Fuller test would be biased in favour of the null. We therefore apply the test to Δp_t instead; this variable is designated 'monthly inflation' in the table. The stationarity of $\Delta\, p_t$ entails the stationarity of $\Delta_{12}\, p_t$.

[A2] That is, $gnc_t = \Delta nc_t$.

A2. The Unrestricted Regression Results

Table A2 reports the parameters of the unrestricted model, estimated by Least Squares. Table A2 includes all of the parameters appearing in equations (1-5) of the main text. Parameters retained in the restricted model in Table 3 of the main text are shown in bold; estimates of these parameters are approximately the same in both tables. It can be seen that application of the Krolzig-Hendry algorithm leads to the exclusion of a small number of parameters that are marginally significant in the unrestricted model, for example, the parameter on rbk_{t-1} in the *rbi* equation. Retention of these parameters in the restricted model does not make any noticeable difference to the response profiles in Figures 4-12 of the main text.

A3. The Robustness of the Restricted Regression Results

Table A3 reports alternative estimates of the parameters of the restricted model, including the SUR estimates in Table 3 of the main text alongside Least Squares and Maximum Likelihood estimates. There are three sets of estimates in each case: the first use no instruments for mil_t and gnc_t, the second use worldwide aid values as instruments, and the third use Latin American aid values as instruments. There is little variation in the parameter estimates across the nine alternatives. A tenth column reports parameters obtained by applying the Least Squares estimator to monthly conflict data excluding the annual totals. (In other words, we replace x_t' on page 12 of the main text with x_t.) Again, this leads to little variation in the parameter estimates.

A4. The Consequences of Extending the Sample Period beyond December 1993

It is possible to fit the Table 3 model to a larger data set, including monthly data for the mid-1990s. Figure A1 provides some information on the effect that this has on the estimated parameters of the model. The figure is based on a set of recursive parameter estimates. First of all, we fit the model to data for January 1983 – December 1992, then to data for January 1983 – January 1993, then to data for January 1983 – February 1993, and so on up to a sample incorporating January 1983 – December 1995. In each case, starting with the January 1983 – January 1993 estimates, we compute Chow Test statistics for the null that the parameters in the extended sample are equal to the parameters in the original January 1983 – December 1992 sample. There is a separate Chow Test for each of the five equations. Figure A1 plots the change in the value of the test statistics as subsequent months are added to the sample. There are five charts in the table, one for each equation; the vertical axes measure the test statistic as a fraction of its 5% critical value.[A3]

It can be seen that there is no significant change in the parameters of the *pgi*, *pgk* and *civ* equations, that is, the part of the model relating to the behavior of government forces. However, if we extend the sample into 1994, the Chow Tests reject the null that the parameters of the *rbi* and *rbk* equations are constant. Rebel behavior does change significantly in 1994, probably as a result of the repentance law. Given this instability in the parameter estimates, our discussion in the main text is based on estimates of the model fitted to data for January 1983 – December 1993.

[A3] Figure A1 shows the Chow Test results using the model in column 3 of Table A3, but this choice is not crucial to our results.

Table A1: Augmented Dickey-Fuller Test Statistics

(i) Monthly Variables

The regressions include a deterministic seasonal term, and for *rbi* a dummy for April 1986.

variable	*sample*	*ADF t ratio*	*number of lags included*
pgi	Jan. 1983 – Dec.1993	-3.07	2
pgk	Jan. 1983 – Dec.1993	-4.30	2
civ	Jan. 1983 – Dec.1993	-3.74	3
rbi	Jan. 1983 – Dec.1993	-2.91	2
rbk	Jan. 1983 – Dec.1993	-3.24	2
monthly inflation	Jan. 1983 – Dec.1993	-2.73	3

(ii) Annual Variables

The regressions include an intercept.

variable	*sample*	*ADF t ratio*	*number of lags included*
mil	1961-2008	-2.37	0
oda	1963-2008	-4.17	0
nc	1976-2008	-1.66	1
gnc	1976-2008	-8.73	0

Table A2: Unrestricted Least Squares Regression Results

Effects retained in the restricted model are written in bold type.

	pgi equation		*pgk* equation		*civ* equation		*rbi* equation		*rbk* equation	
	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	t ratio
pgi_{t-1}	**0.303**	**2.36**	**0.802**	**2.72**	-0.033	-0.11	coeff.	*t ratio*	-0.002	-0.01
pgi_{t-1}	0.192	1.44	0.021	0.07	0.096	0.29	-0.064	-0.55	**0.399**	**1.40**
pgi_{t-3}	**0.329**	**2.41**	**0.760**	**2.42**	**0.837**	**2.49**	0.234	1.89	**0.328**	**1.12**
pgi_{t-4}	0.188	1.42	0.324	1.06	0.145	0.45	0.220	1.77	0.140	0.50
pgk_{t-1}	0.060	1.38	-0.133	-1.34	0.169	1.58	0.006	0.05	-0.030	-0.33
pgk_{t-1}	-0.076	-1.75	-0.166	-1.67	0.092	0.86	-0.010	-0.26	0.077	0.83
pgk_{t-3}	-0.035	-0.77	0.053	0.51	-0.081	-0.73	-0.060	-1.52	0.028	0.29
pgk_{t-4}	-0.060	-1.35	**-0.305**	**-2.97**	-0.106	-0.97	-0.029	-0.72	0.021	0.22
civ_{t-1}	-0.048	-0.91	-0.179	-1.46	0.015	0.11	0.058	0.94	-0.111	-0.97
civ_{t-2}	-0.078	-1.48	-0.069	-0.57	-0.160	-1.23	-0.018	-0.37	-0.165	-1.46
civ_{t-3}	**-0.158**	**-3.08**	**-0.405**	**-3.44**	**-0.375**	**-2.98**	-0.042	-0.87	**-0.251**	**-2.29**
civ_{t-4}	-0.064	-1.18	-0.218	-1.76	-0.056	-0.42	-0.080	-1.70	-0.200	-1.73
rbi_{t-1}	0.042	0.30	-0.407	-1.24	-0.466	-1.33	**0.367**	**3.05**	0.241	0.79
rbi_{t-1}	0.135	0.94	-0.361	-1.09	0.241	0.68	**0.157**	**1.21**	**0.384**	**1.25**
rbi_{t-3}	-0.106	-0.78	-0.079	-0.25	0.056	0.17	-0.034	-0.26	0.192	0.66
rbi_{t-4}	-0.011	-0.08	**0.655**	**2.23**	0.118	0.38	**0.217**	**1.72**	0.159	0.58
rbk_{t-1}	**0.112**	**1.67**	0.233	1.51	**0.381**	**2.31**	-0.086	-2.11	0.001	0.01
rbk_{t-1}	-0.006	-0.09	**0.412**	**2.64**	-0.219	-1.31	-0.006	-0.11	-0.182	-1.25
rbk_{t-3}	**0.143**	**2.11**	0.247	1.59	**0.265**	**1.59**	0.013	0.20	0.053	0.36
rbk_{t-4}	0.163	2.44	0.179	1.17	-0.024	-0.14	0.004	0.07	-0.013	-0.09
mil_{t}	0.001	0.02	0.029	0.36	0.124	1.45	0.039	1.19	0.061	0.82
mil_{t-12}	-0.013	-0.37	0.058	0.70	-0.149	-1.69	**0.058**	**1.82**	-0.075	-0.98
oda_{t}	-0.398	-1.37	-0.797	-1.19	-1.096	-1.53	-0.238	-1.73	-0.366	-0.59
oda_{t-12}	0.061	0.21	0.088	0.13	1.24	1.72	**-1.146**	**-4.31**	0.977	1.56
gnc_{t}	**-0.223**	**-1.59**	**-0.338**	**-1.05**	**-0.779**	**-2.26**	0.005	0.16	-0.471	-1.57
gnc_{t-12}	**-0.390**	**-2.59**	**-0.828**	**-2.39**	**-0.881**	**-2.38**	-0.007	-0.05	-0.502	-1.56
inf_{t}	0.019	0.54	**-0.099**	**-1.20**	**0.162**	**1.83**	-0.216	-1.27	0.061	0.80
cgz_{t}	0.059	0.32	**-0.840**	**-1.94**	0.127	0.28	-0.126	-2.58	**-0.466**	**-1.16**
April 1986							**-1.361**	**-3.84**		

Table A3: Regression Results Using Different Estimators and Instruments for US Intervention

	no instruments for US intervention						world instruments for US intervention						Lat. American instruments for US intervention						*using monthly*	
	(1) LS		(2) SUR		(3) ML		(4) LS		(5) SUR		(6) ML		(7) LS		(8) SUR		(9) ML		*data only*	
<u>pgi</u> <u>equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-1}	0.425	*5.58*	0.399	*6.48*	0.399	*6.60*	0.427	*5.61*	0.411	*6.62*	0.411	*7.25*	0.414	*5.47*	0.399	*6.46*	0.399	*6.98*	0.449	*5.87*
pgi_{t-3}	0.331	*3.41*	0.335	*3.68*	0.336	*3.89*	0.339	*3.48*	0.354	*3.87*	0.355	*4.21*	0.321	*3.35*	0.337	*3.71*	0.337	*3.86*	0.277	*2.85*
civ_{t-3}	-0.143	*-2.99*	-0.129	*-2.79*	-0.128	*-2.80*	-0.152	*-3.15*	-0.142	*-3.03*	-0.142	*-3.12*	-0.146	*-3.08*	-0.135	*-2.95*	-0.135	*-2.84*	-0.114	*-2.28*
rbk_{t-1}	0.138	*2.98*	0.124	*2.80*	0.121	*2.87*	0.137	*2.94*	0.118	*2.66*	0.115	*2.77*	0.149	*3.22*	0.129	*2.96*	0.126	*2.99*	0.158	*3.35*
rbk_{t-3}	0.133	*2.71*	0.112	*2.40*	0.110	*2.01*	0.143	*2.89*	0.116	*2.49*	0.113	*2.06*	0.150	*3.06*	0.124	*2.68*	0.121	*2.24*	0.132	*2.62*
gnc_t	-0.188	*-2.17*	-0.202	*-2.41*	-0.204	*-2.42*	-0.301	*-2.36*	-0.295	*-2.30*	-0.299	*-2.33*	-0.400	*-2.80*	-0.371	*-2.61*	-0.378	*-2.65*	-0.215	*-2.41*
gnc_{t-12}	-0.250	*-3.07*	-0.246	*-3.13*	-0.247	*-3.83*	-0.172	*-2.34*	-0.163	*-2.28*	-0.163	*-2.52*	-0.192	*-2.64*	-0.176	*-2.48*	-0.178	*-2.83*	-0.258	*-3.10*
σ	0.329		0.330		0.330		0.322		0.297		0.330		0.318		0.264		0.327		0.336	
<u>pgk</u> <u>equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-1}	0.418	*2.31*	0.462	*2.63*	0.464	*2.91*	0.474	*2.59*	0.519	*2.92*	0.523	*2.98*	0.483	*2.63*	0.522	*2.92*	0.526	*2.96*	0.455	*2.47*
pgi_{t-3}	0.761	*3.16*	0.711	*3.04*	0.686	*3.05*	0.769	*3.12*	0.725	*3.04*	0.696	*3.14*	0.760	*3.08*	0.723	*3.02*	0.691	*3.10*	0.666	*2.69*
pgk_{t-4}	-0.289	*-3.34*	-0.249	*-3.04*	-0.235	*-3.00*	-0.289	*-3.26*	-0.245	*-2.95*	-0.230	*-2.99*	-0.289	*-3.24*	-0.249	*-2.97*	-0.234	*-3.11*	-0.270	*-3.10*
civ_{t-3}	-0.398	*-3.74*	-0.373	*-3.59*	-0.367	*-4.41*	-0.384	*-3.51*	-0.363	*-3.39*	-0.355	*-3.92*	-0.373	*-3.43*	-0.352	*-3.31*	-0.343	*-3.87*	-0.391	*-3.47*
rbi_{t-4}	0.632	*2.93*	0.555	*2.72*	0.554	*2.72*	0.582	*2.65*	0.504	*2.44*	0.503	*2.29*	0.583	*2.62*	0.489	*2.33*	0.489	*2.16*	0.616	*2.66*
rbk_{t-2}	0.266	*2.39*	0.224	*2.13*	0.214	*1.91*	0.276	*2.42*	0.232	*2.17*	0.221	*2.05*	0.281	*2.46*	0.243	*2.26*	0.233	*2.14*	0.281	*2.44*
gnc_t	-0.466	*-2.37*	-0.477	*-2.48*	-0.491	*-2.62*	-0.293	*-1.01*	-0.296	*-1.02*	-0.304	*-1.05*	-0.207	*-0.57*	-0.166	*-0.45*	-0.155	*-0.43*	-0.424	*-2.06*
gnc_{t-12}	-0.712	*-3.69*	-0.685	*-3.63*	-0.684	*-4.71*	-0.502	*-2.89*	-0.468	*-2.76*	-0.456	*-3.04*	-0.514	*-2.89*	-0.467	*-2.69*	-0.453	*-2.86*	-0.639	*-3.21*
inf_t	-0.174	*-2.94*	-0.183	*-3.25*	-0.186	*-3.85*	-0.184	*-3.04*	-0.193	*-3.35*	-0.196	*-3.97*	-0.189	*-2.96*	-0.188	*-3.12*	-0.191	*-3.79*	-0.204	*-3.26*
cgz_t	-0.907	*-4.14*	-0.953	*-4.59*	-0.951	*-5.62*	-0.893	*-3.92*	-0.919	*-4.28*	-0.903	*-4.78*	-0.912	*-3.56*	-0.903	*-3.74*	-0.880	*-4.24*	-1.047	*-4.59*
σ	0.718		0.720		0.721		0.718		0.354		0.737		0.720		0.734		0.738		0.742	
<u>civ</u> <u>equation</u>	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-3}	0.742	3.77	0.734	3.76	0.739	3.65	0.752	3.90	0.762	3.99	0.767	3.96	0.693	3.50	0.706	3.59	0.711	3.37	0.790	4.02
civ_{t-3}	-0.324	-2.89	-0.298	-2.70	-0.299	-2.92	-0.352	-3.18	-0.337	-3.09	-0.338	-3.40	-0.312	-2.79	-0.299	-2.72	-0.300	-2.87	-0.353	-3.00
rbk_{t-1}	0.266	2.48	0.245	2.34	0.240	1.92	0.262	2.50	0.232	2.26	0.225	1.83	0.299	2.81	0.265	2.55	0.257	2.01	0.273	2.53
rbk_{t-3}	0.314	2.79	0.287	2.61	0.280	2.23	0.345	3.14	0.311	2.88	0.304	2.48	0.356	3.18	0.320	2.91	0.311	2.52	0.309	2.72
gnc_t	-0.524	-2.64	-0.482	-2.48	-0.478	-2.49	-1.073	-3.49	-1.040	-3.40	-1.047	-3.42	-0.953	-2.91	-0.925	-2.84	-0.944	-2.89	-0.521	-2.56
gnc_{t-12}	-0.560	-3.03	-0.538	-2.98	-0.542	-2.74	-0.333	-2.02	-0.334	-2.08	-0.343	-2.18	-0.380	-2.27	-0.381	-2.33	-0.394	-2.37	-0.586	-3.11
inf_t	0.125	2.32	0.107	2.43	0.110	3.16	0.106	2.02	0.099	2.29	0.102	3.17	0.093	1.74	0.093	2.10	0.096	3.02	0.129	2.34
σ	0.762		0.763		0.763		0.731		0.475		0.748		0.743		0.603		0.761		0.775	

Table A3 (Continued)

	no instruments for US intervention						world instruments for US intervention						Lat. American instruments for US intervention						*using monthly data only*	
	LS		SUR		ML		LS		SUR		ML		LS		SUR		ML			
rbi equation	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-4}	0.136	*2.27*	0.152	*3.00*	0.154	*3.54*	0.103	*1.66*	0.129	*2.41*	0.135	*3.04*	0.113	*1.84*	0.135	*2.56*	0.139	*3.14*	0.112	*2.00*
rbi_{t-1}	0.257	*3.18*	0.194	*2.90*	0.187	*2.66*	0.350	*4.43*	0.279	*4.14*	0.259	*3.32*	0.321	*4.02*	0.255	*3.80*	0.242	*3.08*	0.278	*3.46*
rbi_{t-3}	0.241	*3.12*	0.233	*3.58*	0.225	*2.84*	0.281	*3.50*	0.263	*3.83*	0.247	*3.04*	0.249	*3.10*	0.238	*3.47*	0.228	*2.88*	0.248	*3.12*
mil_t	0.061	*3.54*	0.059	*3.90*	0.056	*3.79*	0.031	*1.63*	0.027	*1.51*	0.020	*1.11*	0.053	*2.66*	0.045	*2.31*	0.038	*1.98*	0.060	*3.48*
oda_t	-0.754	*-4.03*	-0.726	*-4.60*	-0.716	*-4.73*	-0.468	*-2.69*	-0.439	*-3.00*	-0.435	*-3.02*	-0.475	*-2.77*	-0.449	*-3.12*	-0.448	*-3.31*	-0.754	*-3.95*
April 1986	-1.577	*-4.99*	-1.052	*-4.02*	-0.923	*-8.07*	-1.522	*-4.60*	-0.992	*-3.56*	-0.827	*-6.68*	-1.579	*-4.81*	-1.046	*-3.80*	-0.889	*-6.75*	-1.561	*-4.89*
σ	0.292		0.297		0.300		0.299		0.112		0.316		0.295		0.370		0.312		0.294	
rbk equation	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*	coeff.	*t ratio*
pgi_{t-2}	0.316	1.81	0.163	1.12	0.125	1.02	0.316	1.81	0.162	1.10	0.112	0.91	0.316	1.81	0.156	1.06	0.112	0.88	0.328	1.88
pgi_{t-3}	0.411	2.02	0.353	2.02	0.335	2.97	0.411	2.02	0.368	2.08	0.343	2.88	0.411	2.02	0.368	2.09	0.348	2.96	0.419	2.07
civ_{t-3}	-0.188	-2.03	-0.117	-1.48	-0.102	-1.57	-0.188	-2.03	-0.128	-1.61	-0.108	-1.73	-0.188	-2.03	-0.130	-1.63	-0.112	-1.79	-0.202	-2.10
rbi_{t-2}	0.328	1.82	0.364	2.37	0.371	2.52	0.328	1.82	0.355	2.29	0.361	2.39	0.328	1.82	0.362	2.34	0.364	2.37	0.316	1.70
cgz_t	-0.520	-2.87	-0.411	-2.51	-0.365	-2.12	-0.520	-2.87	-0.256	-1.60	-0.156	-1.02	-0.520	-2.87	-0.290	-1.78	-0.212	-1.23	-0.531	-2.90
σ	0.662		0.667		0.670		0.647		0.704		0.678		0.647		0.692		0.675		0.668	

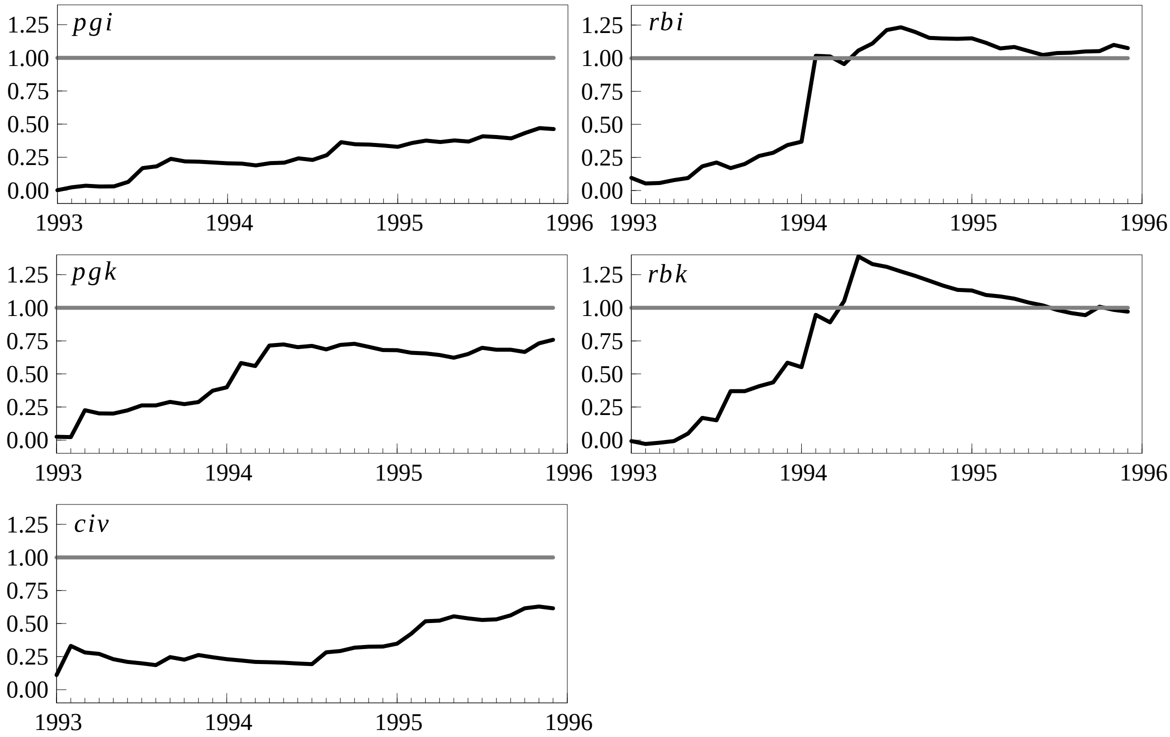

Figure A1: Recursive Chow Test Statistics as a Fraction of the 5% Critical Value