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Methods for Measuring Aggregate Costs of Conflict

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Abstract

This paper reviews the methods for measuring the economic cost of conflict. Estimating the economic costs of conflict requires a counterfactual calculation, which makes this a very difficult task. Social researchers have resorted to different estimation methods depending on the particular effect in question. The method used in each case depends on the units being analyzed (firms, sectors, regions or countries), the outcome variable under study (aggregate output, market valuation of firms, market shares, etc.) and data availability (a single cross-section, time series or panel data). This paper reviews existing methods used in the literature to assess the economic impact of conflict: cost accounting, cross-section methods, time series methods, panel data methods, gravity models, event studies, natural experiments and comparative case studies. The paper ends with a discussion of cost estimates and directions for further research.

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Abstract

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1 Introduction

Conflict manifests itself in several forms, from strikes, demonstrations and riots to guerrilla warfare, terrorism and civil war. In turn, these forms of conflict have economic, social, psychological and other types of costs. Notwithstanding the importance of the other types of costs, this paper focuses on measuring the economic costs of conflict at the aggregate level.

Estimating the economic cost of conflict is a difficult task. It amounts to calculating what a given economic magnitude, say GDP, would have been in the absence of conflict - a counterfactual calculation that is difficult to carry out. Conflict itself is an unobservable magnitude, which makes statistical inference problematic as researchers have to resort to proxy indicators of the level of conflict such as the number of casualties in a war or the number of political assassinations. Therefore, it is not surprising that, despite its relevance, the issue has received little attention relative to other topics. Recent events, such as September 11-th and the war in Iraq, have triggered a new surge in this area of research. While estimating the magnitude of the economic costs of conflict remains an unsettled question, the empirical evidence surveyed in this article suggests that the costs are significant and sizable.

In studying the economic cost of conflict, we will distinguish among various types of costs. Economic costs can be classified into direct and indirect costs. For example, a civil war has a direct economic cost equal to all property destroyed plus an indirect cost that includes the production loss during and after the conflict due to casualties and capital destruction during the conflict. Analyzing the temporal dimension, we can classify the economic costs of conflict into contemporaneous and accumulated costs. The contemporaneous costs, also referred to as impact costs, are those incurred in the same period as the conflict. The accumulated or long-run cost is the sum of the contemporaneous costs and the discounted value of future costs.

The methods used are diverse and range from time series methods to cross-section and panel data methods. The methods used in the literature are determined by the objective of the study and data availability. When the objective is to assess the economic cost of conflict in a particular country, region or sector, time series methods are typically used, while when the purpose is to asses the economic impact of conflict for a set of countries, researchers use panel data methods.

In this survey, we review the different methods used in the literature to estimate the economic effect of conflict. There are other interesting discussions on the economic costs of violence, e.g. Skaperdas (forthcoming), while ours focuses on methods. Section 2 reviews the method of cost accounting. Section 3 comments on regression methods using cross-section data. Section 4 examines the contribution of time series methods, in particular interrupted time series, transfer function and vector autorregresion methods. Regression methods using panel data are reviewed in section 5. Section 6 covers event studies from financial economics. Section 7 reviews natural experiments. Section 8 reviews the comparative case study method. Finally, section 9 ends with a discussion and offers a view of the road ahead.

2 The cost accounting method

The cost accounting method is probably the simplest and more straightforward method of estimating the economic cost of conflict. It simply adds up the monetary value of direct and indirect costs. Direct costs estimates are based on actual data from public accounts and statistical records. The estimates of the indirect costs of conflict include costs such as the production loss due to capital destruction and the compounded value of subsequent production loss during the post-conflict period. Production loss estimates are subject to criticism as they require some counterfactual estimate, typically from a regression model, plus some hypothesis about the interest rate to be applied to calculate the compounded value.

A good example of this approach is the Arunatilake, Jayasuriya and Kelegama (2001) estimates of the cost of civil war in Sri Lanka over the 1984-1996 period. They estimate both direct and indirect costs. The direct cost estimates of a given magnitude are obtained by comparing actual figures with an educated guess of what the magnitude would have been in the absence of conflict. According to their estimates, the direct cost of war in Sri Lanka was 61.9 percent of Sri Lanka's 1996 GDP or over six billion US dollars at the then prevailing exchange rate. This estimate includes the extra government military spending due to the war (41.3 percent of Sri Lanka's 1996 GDP), the Liberation Tigers of Tamil Eelam (LTTE) military spending (4.1 percent), the cost of providing for the refugees (3 percent) and damages to capital assets and land (13.5 percent). Using counterfactuals obtained from estimated regressions and plausible scenarios, they also provide indirect costs estimates of the conflict due to foregone investment (8.61 percent), reduced tourist arrivals (17 percent), foregone foreign investment (71.2 percent), human capital of dead or injured persons (2.5 percent) and other costs. Total direct and indirect costs added up to 168 percent of Sri Lanka's 1996 GDP.

The cost accounting method has also been applied to the evaluation of the economic cost of participating in a war. Davis, Murphy and Topel (2006) estimated the pre-invasion present value cost of the war in Iraq for the United States. These costs included military resources, the value of lost lives and injuries sustained by U.S. soldiers, the lifetime medical costs of treating injured soldiers and humanitarian assistance and post-war reconstruction. They estimated the annual cost of war under different scenarios and then computed the present value using various discount schemes. Their estimated cost of the war in Iraq for the U.S. ranged from 100 to 870 billions of 2003 U.S. dollars (0.9 to 7.8 percent of the U.S. GDP). In another paper, Bilmes and Stiglitz (2006) using a similar methodology estimated that the total economic costs of the war in Iraq for the U.S. would range from one trillion using a conservative scenario to three trillion U.S. dollars using a moderate scenario.

The cost accounting methodology provides costs estimates that are numerically easy to perform and the calculations can be carried out for a multiplicity of scenarios. On the negative side, the cost accounting methodology requires expertise in listing all types of costs; otherwise the list might not be exhaustive and some costs could be left out or double counted. In addition,

the design of different scenarios is problematic as they are not accompanied by their likelihood. From a statistical point of view, the cost accounting method does not allow the researcher to perform statistical inference as the estimates do not come with standard errors.

3 Inference based on cross-section data

A simple way to asses the economic effect of conflict is by means of a simple regression model. A regression equation is often postulated where some economic variable, the outcome, is regressed on a measure of conflict and other control variables. When a cross-section data set on these variables is available, one can exploit the cross-section variation in the conflict measurement to asses its effect on the outcome variable. The quantitative value of these estimates can be interpreted as a calculation of the effect of conflict on the average unit of analysis. Some examples of this approach follow.

Venieris and Gupta (1986) provide a neat example of this methodology. They claim that socio-political instability, an index composed by the number of deaths, protest demonstrations and regime type, negatively affects savings. Using a sample of 49 non communist countries, they report the following estimates[1]

$$\frac{S}{Y} = \underset{(-3.27)}{-0.022}\, SPI + other\ covariates$$

where the left hand side variable is the savings to GDP ratio and SPI stands for Socio-Political Instability. This evidence supports the hypothesis that higher socio-political instability results in lower savings. The fact that the socio-political instability variable is an index poses a problem when evaluating its quantitative effect on the savings ratio as we do not know how to interpret a change in the SPI index. An interpretation of the effect of the SPI index is possible using the standard deviation of the index. Unfortunately, the authors do not report descriptive statistics on the SPI index and therefore we cannot state precisely the quantitative effect of socio-political instability on the savings to GDP ratio.

A quantitative estimate of the effect of socio-political instability on investment is feasible, however, in a second example of this approach by Alesina and Perotti (1996). They argue that the level of socio-political instability, an index reflecting political assassinations, coups and other variables, should affect investment negatively. Using a sample of 71 countries and sample averages of the period 1960-1985, they report the following estimated equation

$$\frac{I}{Y} = \underset{(-2.39)}{-0.50}\, SPI + other\ covariates$$

where the left hand side variable is the investment to GDP ratio and SPI stands for socio-political instability. Alesina and Perotti note that there exists the possibility of reverse causation

[1] Hereinafter figures within parentheses are t statistics.

from investment to socio-political instability. To avoid the reverse causation bias, Alesina and Perotti used instrumental variable estimators. The regression coefficient estimates are meaningless unless the scale of the explanatory variable is specified. This poses a problem when the explanatory variable is an index, as in the present case. One way of conducting a simple quantitative assessment of the impact of the SPI index on the investment ratio is as follows. Alesina and Perotti report a standard deviation of the SPI index of 11.95. To give an idea of what this magnitude means, 11.95 would be the increase in the index of socio-political instability when we compare the level of socio-political instability in the USA to that of Chile. A one standard deviation increase in the index of socio-political instability would generate a fall in investment of $0.5 \times 11.95 = 5.975$ percentage points in the investment to GDP ratio.[2] This quantitative value requires two remarks. First, a one standard deviation change in the SPI index is a change in this index from a low value of SPI to a high value of SPI that could be difficult to observe in any particular country in a short period of time. Second, this cross-section estimate of the cost of conflict represents an average of the effect over countries. Therefore, particular conflict episodes can have smaller or larger impacts on the investment ratio.

In his highly cited paper, Barro (1991) studied the sources of economic growth empirically for a sample of 98 countries. He reports the following estimates

$$\Delta y_i = \underset{(-6.25)}{-0.0075} y_{0i} \underset{(-3.10)}{-0.0195} REV_i \underset{(-2.15)}{-0.0333} ASSASS_i + other\ covariates$$

$$\left(\frac{I}{Y}\right)_i = \underset{(-2.04)}{-0.0098} y_{0i} \underset{(-2.62)}{-0.055} REV_i \underset{(-2.52)}{-0.068} ASSASS_i + other\ covariates$$

where Δy_i is the average per capita rate of growth of country i over the 1960-1985 period, $\left(\frac{I}{Y}\right)_i$ is the average over the same period of the private investment to GDP ratio, y_{0i} is the initial per capita GDP, *REV* measures the number of revolutions and coups per year and *ASSASS* records the number of political assassinations per million population per year. To avoid the problem of reverse causation from growth to political instability Barro uses the instrumental variables estimation technique. According to his findings, *REV* and *ASSASS* are measures of political instability negatively associated with growth. Using the standard deviations of these variables we can again compute the quantitative effect. A one standard deviation increase in the number of revolutions and coups per year reduces per capita growth rate by almost half a percentage point $(-0.0195 \times 0.23 = -0.0045)$ and private investment to GDP ratio by 1.26 percentage points $(-0.055 \times 0.23 = -0.0126)$. Similarly, a one standard deviation increase in the number of political assassinations per million population per year reduces per capita growth rate by 0.29 percentage points $(-0.0333 \times 0.086 = -0.0029)$ and the investment ratio by 0.58 percentage points $(-0.068 \times 0.086 = -0.0058)$.

[2]Multiplying the coefficient estimate by the standard deviation of the explanatory variable is equivalent to computing regression coefficients on standardized explanatory variables, a technique often used to compare the effects of different explanatory variables.

Abadie and Gardeazabal (2008) analyze the effect of terrorism on the net foreign direct investment position in a sample of 98 countries in 2003. They report the following estimates

$$\frac{NFDI\ position}{Y} = \underset{(-2.0833)}{-\ 0.0025}\ GTI + other\ covariates$$

where the left hand side variable is the net foreign direct investment position (domestic assets owned by foreign investors minus foreign assets held by domestic investors) over GDP and GTI is a Global Terrorism Index. The standard deviation of the terrorism index is 19.82. A one standard deviation change in this index would be the change in terrorist risk if we compare Italy with the United States (Italy having a lower terrorist risk). According to their findings, a one standard deviation increase in terrorist risk induces a fall in the net foreign direct investment position over GDP ratio of $0.0025 \times 19.82 = 0.0495$, almost 5 percentage points.

Interestingly, Koubi (2005) studied the effect of war on growth both during the war and post-war periods. She reports the following cross-country growth regressions for a sample of 78 countries

$$\Delta y_{60-89} = \underset{(-1.87)}{-0.266} \times BD_{60-89} + other\ covariates$$

$$\Delta y_{75-89} = \underset{(1.94)}{3.25} \times BD_{60-74} + other\ covariates$$

where Δy_{60-89} and Δy_{75-89} stand for the average annual rate of real per capita growth during the period 1960-1989 and 1975-1989 respectively and BD_{60-74} and BD_{60-89} are the number of battle deaths in the 1960-1974 and 1960-1989 periods.[3] Her findings indicate that contemporaneous effect of war on growth is negative, but the effect of war on the subsequent growth rate during the post-war period is positive, the so called "peace dividend" effect. Koubi reports a standard deviation of the battle deaths variable of 230,635.3, which can be used to compute a quantitative value of the cost of conflict. A one standard deviation increase in the number of battle deaths during the thirty year period would result in an average growth rate fall of 0.61 percentage points ($-0.266 \times 10^{-7} \times 230,635.3 = 0.0061$), more than half a percentage point lower growth rate over a thirty year period.

Inference based on cross-section data suffers from some drawbacks. First, it is typically the case that several covariates can be jointly determined with the dependent variable or causality might run backwards (reverse causation) and, therefore, parameter estimates might suffer from the endogeneity bias. In order to circumvent this problem instrumental variables estimators can be used. This is the approach followed by Alesina and Perotti (1996) and Barro (1991). Second, the estimated economic effects of conflict using cross-section datasets are to be interpreted as averages over units of analysis. Therefore, particular conflict episodes can have smaller or larger impacts. Third, cross-section inference forces researchers to adopt a static specification

[3]The actual values reported by Koubi (2005) are those reported above times 10^{-7}.

and cannot study the dynamic effect of conflict on the outcome.

4 Inference using time series

Time series methods have been used in the past to assess the economic impact of conflict, particularly terrorism. The identification strategy exploits the time variation of the conflict measurement for a single unit (region or country). These methods have been applied to aggregate figures such as per capita gross domestic product and bilateral international trade flows as well as to sectoral figures such as tourism revenue. Three approaches have been used in the past: the interrupted time series approach, the transfer function and vector autorregresions.

4.1 The interrupted time series approach

The Interrupted Time Series (ITS) approach, sometimes called quasi-experimental time series analysis, is a research technique designed for analyzing different types of interventions or policies. This methodology requires availability of time series data on the outcome for each subject. Although the analysis is more robust when several subjects are analyzed, the method can be applied to a single subject.

In the analysis of the economic effect of conflict, the intervention analyzed is a particular conflict episode. A simple ITS model postulates that the outcome variable, y_t, can be represented as

$$y_t = \beta_0 + \beta_1 \times Intervention\ Level_t + \beta_2 \times Trend_t + \beta_3 \times Intervention\ Trend_t + \varepsilon_t, \quad (1)$$

where $Intervention\ Level_t$ is a dummy variable equal to 1 during the intervention (conflict) period and zero otherwise, $Trend_t$ is a count variable equal to 1 in the first period of the sample, 2 in the second and so on, $Intervention\ Trend_t$ is a count variable equal zero from the beginning of the sample to the start of the intervention, equal to 1 in the first period of the intervention period, 2 in the second and so on and ε_t is a zero mean uncorrelated disturbance. A significant value of β_1 indicates a level change after the intervention, whereas a significant value of β_3 indicates a trend change after the intervention.

Anderson and Carter (2001) applied the ITS approach to analyze the effect of war on international trade. Their specification was slightly different from (1), considering two interventions: war and peace. They report ITS estimates for fourteen war episodes. For instance, using annual data for France-Germany bilateral trade (real exports plus imports) for the 1904-1928 period and considering the 1914-1918 war and subsequent peace, Anderson and Carter report the following estimates

$$\ln(France/Germany\ Trade)_t = \underset{(16.74)}{7.03} + \underset{(0.75)}{0.06} \times Trend_t - \underset{(1.41)}{1.21} \times War\ Level_t$$

$$\underset{(5.63)}{-1.35} \times War\ Trend_t + \underset{(9.19)}{6.80} \times Peace\ Level_t + \underset{(5.71)}{1.37} \times Peace\ Trend_t + \varepsilon_t. \quad (2)$$

According to these results, the 1914-1918 France-Germany war resulted in a significant fall in the international trade trend and a significant increase in the level and trend during the post-conflict peace period. Interestingly, the war and peace trends have almost the same impact with different signs.

Equation (1) is probably the simplest ITS model, postulating a very simple time series representation of the outcome variable as a trend plus noise model enhanced with level and trend intervention variables. More sophisticated ITS models could accommodate other covariates, seasonal components and serial correlation of the disturbance term, thus allowing for a more flexible time series representation of the outcome variable.

ITS methods allow the researcher to make inference on the time evolution of the outcome after the intervention. In particular, ITS allows for changes in the level and trend in the outcome, something that is not the case with other methodologies. ITS requires the exact moment to be established when the intervention starts and ends, creating a problem when considering conflict as an intervention, as it is difficult to determine exactly when a particular conflict starts or ends. In addition, the artificially constructed level and trend intervention variables assume that the intensity of the conflict is constant over the conflict period, an assumption that might not tally with many conflict episodes.

4.2 The transfer function approach

In contrast with ITS, the transfer function approach resorts to measurements of conflict, such as number of casualties, political assassinations, etc. It thus avoids the exact dating of the conflict period and allows for different degrees of conflict over time. The transfer model provides a framework for the quantitative assessment of the contemporaneous economic impact of conflict as well as the dynamic period by period effect and the long-run accumulated effect. As an example, consider the simplest of all possible transfer functions

$$y_t = ay_{t-1} + bx_t + \varepsilon_t, \quad (3)$$

where the outcome variable, y_t, depends on its own lag, y_{t-1}, the contemporaneous value of the conflict measurement, x_t, and a zero mean shock, ε_t. Suppose that the conflict measurement experiments a unit increase in period t and returns to its original level from time $t+1$ onwards. The contemporaneous response of the outcome variable equals b, at time $t+1$ the outcome increases by ab, at time $t+2$ by a^2b, at time $t+3$ by a^3b, and so on. Under the assumption that parameter a is smaller than unity in absolute value, the outcome variable time series is stationary and we can compute the accumulated response to a unit increase in conflict measurement as $b(1+a+a^2+a^3+...) = b/(1-a)$. Therefore, the response of the outcome variable is higher the larger the value of b and this response is more persistent the closer the value of a to unity.

Theoretically, the value of b should be negative, that is, an increase in the conflict measurement should reduce the outcome variable.

A general transfer model is

$$y_t = \frac{B(L)}{A(L)}x_t + \frac{C(L)}{D(L)}\varepsilon_t \tag{4}$$

where y_t is the outcome variable such as per capita GDP, x_t is a measure of conflict intensity, $A(L)$, $C(L)$ and $D(L)$ are polynomials of the form $A(L) = 1 - a_1L - a_2L^2 - .... - a_pL^p$, L is the lag operator, $B(L) = b_0 - b_1L - b_2L^2 - .... - b_qL^q$ and ε_t is a zero-mean white noise. It is easy to see that equation (3) can be obtained from equation (4) assuming $A(L) = D(L) = 1 - aL$, $B(L) = b$ and $C(L) = 1$.

The transfer function methodology is a powerful tool for measurement and provides a simple interpretation of the dynamics of the cost of conflict. Some selective applications of this methodology follow. In an influential paper, Enders, Sandler and Parise (1992) used transfer function analysis to estimate the effect of transnational terrorism on tourism receipts in Greece, Italy and Austria during the 1968-1988 period. Their outcome variable y_t was the (log) share of quarterly tourism revenues relative to that of all other countries in the sample (the market share). Their measure of terrorism, x_t, was the number of transnational terrorism incidents. For the case of Greece, Enders et al. (1992) estimated a transfer function of the form

$$y_t = \underset{(7.39)}{0.7085}y_{t-1} - \underset{(-2.23)}{0.0064}x_{t-3} + \varepsilon_t - \underset{(3.19)}{0.4076}\varepsilon_{t-4}.$$

According to their findings, a unit increase in the number of terrorism incidents, x_t, reduces Greece's tourism market share by the amount of 0.0064 three quarters later. The reason for this delay in the response, the authors argue, is that "it takes time for tourists to revise their plans; many reservations on airlines and cruise ships cannot be altered without paying a sizable premium." Therefore, an additional terrorist incident in Greece resulted in a fall in the (log of) Greece's tourism market share of 0.0064 ($e^{0.0064} = 1.0064$ percentage loss of market share), three quarters later, $0.0064 \times 0.7085 = 0.0045$ ($e^{0.0045} = 1.0045$ percentage loss of market share) four quarters later, and so on.[4]

Another application of the transfer function approach is Enders and Sandler (1996) where they analyze the effect of terrorism on Foreign Direct Investment (FDI). By inducing a sense of fear and heightened financial risks, terrorism can dissuade foreign capital inflows and scare domestic capital away. Using data on net (inflows minus outflows) foreign direct investment in Spain and transnational terrorist incidents during the period 1975-1991, they estimated the following transfer function

$$y_t = \underset{(1.713)}{23.663} - \underset{(-5.989)}{0.593}\, y_{t-1} - \underset{(-2.900)}{23.817}x_{t-11} + \varepsilon_t - \underset{(-3.763)}{0.459}\, \varepsilon_{t-6},$$

[4]Because 0.0064 is the effect of an additional terrorism incident on the conditional mean of the log market share and this is not equal to the log of the conditional mean, exponentiation is only an approximation.

where y_t is the change in net foreign direct investment measured in millions of (real 1990) US dollars and x_t is the number of transnational terrorist incidents. According to their estimates, an additional transnational terrorist incident in Spain leads to a fall of 23.8 millions of US dollars in net FDI into Spain eleven quarters later. Since the estimated coefficient of the first lag of net FDI is negative, the net FDI response to the incident oscillates from negative to positive, and so on. Twelve quarters after the incident, net FDI rises by $23.8 \times 0.593 = 14.113$ millions of US dollars.

The transfer function methodology constitutes a powerful way of conducting an individual case analysis of the economic effect of conflict at the aggregate (country or sector) level and potentially could be used to analyze the microeconomic consequences of conflict, although we have not been able to find any such application in the literature. As compared with the ITS approach, transfer function applications typically provide a better time series representation of the outcome variable by allowing for lags of the outcome and conflict measurements, as well as a flexible disturbance dynamics. Transfer function modelling, however, cannot incorporate other potential determinants of the outcome variable into the analysis, other than the conflict measurement. In addition, the transfer function approach relies on the assumption of strict exogeneity of the conflict measurement, yielding inconsistent estimates when there is reverse causation from the outcome to the conflict variable.

4.3 Vector autorregresions

Another way to model the dynamic interaction between the outcome variable and conflict measurement is the vector autorregresion (VAR) approach. Within this context, both the outcome variable and the conflict measurement as well as possibly other variables are jointly determined by lagged values of all variables considered. The simplest of all VAR models is a two-variable one-lag model for the outcome, y_t, and the conflict measurement, x_t, of the form

$$y_t = a_{11} y_{t-1} + a_{12} x_{t-1} + \varepsilon_{yt} \tag{5}$$

$$x_t = a_{21} y_{t-1} + a_{22} x_{t-1} + \varepsilon_{xt}$$

where the a_{ij}'s are parameters and ε_{yt} and ε_{xt} are zero mean random disturbances which can be contemporaneously correlated. When the set of right hand side variables is the same for all equations and there are no restrictions on the parameters of the VAR, estimation boils down to a simple ordinary least squares regression for each equation. The VAR captures the causal effect of conflict on the outcome through the first equation and also allows for feedback from the economic outcome to the conflict measurement through the second equation.

The VAR technique allows us to estimate the response of the outcome to a shock in the conflict measurement. For illustration, suppose $y_0 = x_0 = 0$; we shock the conflict measurement in one unit, $\varepsilon_{x1} = 1$ and keep all the other shocks equal to zero, $\varepsilon_{x2} = ... = \varepsilon_{xt} = \varepsilon_{y1} = ... =$

$\varepsilon_{yt} = 0$. As a result of this shock, the time path of the outcome would be $y_1 = 0$, $y_2 = a_{12}$, $y_3 = (a_{11} + a_{12})a_{22}$, ... and the time path of the conflict measurement would be $x_1 = 1$, $x_2 = a_{22}$, $x_3 = a_{21}a_{12} + a_{22}^2$, ... These sequences are the Impulse Response Functions (IRF) and can be computed as a function of the coefficients of the VAR. Adding up these responses would give us the accumulated response. Note that, for the shock to have any effect on the outcome, a_{12} must be non-zero. Otherwise, the time pattern of the outcome would be unchanged by the shock. In the latter case, when $a_{12} = 0$, it is said that x_t does not Granger-cause y_t.[5]

Enders and Sandler (1991) postulated a VAR for the number of tourists visiting Spain, n_t, and the number of transnational terrorist incidents in Spain, i_t. Their specification was slightly different from the simplest model (5)

$$n_t = \alpha_1 + A_{11}(L)n_{t-1} + A_{12}(L)i_{t-1} + \varepsilon_{nt}$$

$$i_t = \alpha_2 + A_{21}(L)n_{t-1} + A_{22}(L)i_{t-1} + \varepsilon_{it}$$

where the alphas include a constant term and seasonal dummies and the $A_{ij}(L)$ are polynomials in the lag operator. Using monthly data for the period 1970-1988, they fitted a 12-lag VAR and found that the number of terrorist incidents Granger-caused the number of tourists (that is, they rejected the hypothesis $A_{12}(L) = 0$), but the number of tourists did not Granger-cause the number of terrorist incidents. The VAR model allowed them to compute the impulse response function to a shock in ε_{it}. As a result of a unit shock in the disturbance of the incidents equation, the accumulated response of the number of tourists was that 140,847 tourists did not visit Spain.

In addition to Granger-causality tests and IRF analysis, VARs can be used to generate short term forecasts under different scenarios of the future path of conflict measurements. An application of this short term prediction capability is Eckstein and Tsiddon (2004). They postulated a VAR for the Israeli economy during the 1980-2003 period including (the logs of) four macroeconomic magnitudes, per capita GDP, investment, exports and non-durable consumption. They used a terrorism index as a predetermined right hand side variable in all four equations of the VAR. According to their findings, terrorism had a negative and significant coefficient in all but the consumption equation.[6] Using the estimated VAR up to the third quarter of 2003, Eckstein and Tsiddon simulated the paths of all four variables for the period 2003:4 to 2005:3 under three scenarios: (i) terror stops as of 2003:4, (ii) terror continues until 2004:3 and (iii) terror continues until 2005:3. Under those scenarios, per capita GDP growth would have been 2.5 percent, 0 percent and -2 percent respectively.

Probably as VAR models are easy to estimate, the VAR methodology is very popular and provides an easy way to compute of IRFs, Granger causality tests and short term forecasts. However, VAR methods are bound to be applied to single subject analysis. With higher com-

[5] See Granger (1969).

[6] Note that since all equations include lags of all variables, it is sufficient that the terrorism index is significant in only one equation for it to have effects on all four variables.

puting capabilities and information availability, often researchers have time series information on a set of subjects, that is, a panel data set. We next turn into the analysis of this data type and methods used therein.

5 Panel data methods

Oftentimes, the cost of conflict assessment is attempted using time series data on several countries, i.e. a panel data set. The identification strategy exploits the time and cross-section variation in the level of conflict. This type of data allows the researcher to control for unobserved heterogeneity, something that cannot be accounted for with either time series or cross sections.

The available evidence on the economic effects of conflict using panel data focuses on growth determinants and includes conflict measures as explanatory variables. As their goal is to study the long-run determinants of growth, they use long time spans, decades or five years intervals, as their time unit interval. Their basic specification is

$$\Delta y_{it} = \alpha_t + \gamma_i + X_{it}\beta + \varepsilon_{it} \tag{6}$$

where Δy_{it} is the per capita growth rate of country i over period t, α_t is a period specific unobserved effect, γ_i is a country specific unobserved effect, X_{it} is a $1 \times K$ vector of explanatory variables, β is a conformable vector of parameters and ε_{it} is a zero mean disturbance.

Researchers have used different procedures to account for unobserved heterogeneity: the Seemingly Unrelated Regressions (SUR) procedure, the fixed-effect dummy-variable approach and the Chamberlain (1982) approach. These three methodologies are analyzed next. In addition, a further method of analysis involves three dimensional data structures arising in the study of the effects of conflict on bilateral international trade flows.

5.1 The SUR procedure

The SUR procedure considers the data for each time period (decade) as a cross-section regression and estimates as many equations as time periods (decades). Stacking the observations for, say T, different decades $\Delta Y_i = (\Delta y_{i1}, ..., \Delta y_{iT})'$, $X_i = (X'_{i1}, ..., X'_{iT})'$, $U_i = (\varepsilon_{i1} + \gamma_i, ..., \varepsilon_{iT} + \gamma_i)'$ and the unobserved time effects $\alpha = (\alpha_1, ..., \alpha_T)'$ we form a T-dimensional system

$$\Delta Y_i = \alpha + X_i\beta + U_i$$

that can be estimated by the Seemingly Unrelated Regressions (SUR) procedure. Notice that the effect of the covariates on growth, β, is constrained to be equal across equations (decades). This procedure allows for unobserved random country specific effects, and fixed time effects captured by different period specific intercepts. Two examples of this approach follow.

In their study on growth determinants, Barro and Lee (1994) use a sample of 95 countries over two decades, 1965-1975 and 1975-1985. Thus, they analyze a two periods (decades) panel data set. One of their covariates, the number of revolutions is a measure of conflict similar to the political instability covariates entered in the cross-section regressions discussed above. Using the SUR technique, they report the following estimated equation

$$\Delta y_{it} = \underset{(-2.09)}{-0.0171} revolutions_{it} + other\ covariates$$

where Δy_{it} is the growth rate of per capita GDP of country i over decade t. Therefore, an additional revolution during a decade reduces the average growth rate during a decade in 1.71 per cent points.

Easterly and Levine (1997) use an unbalanced panel of 95 countries over the three decades period 1960-1989 to shed light on the effect of ethnic diversity on growth. Although it was not their goal to measure the effect of conflict on economic growth, their regressions included the average number of political assassinations per capita during a decade as a proxy for the level of political instability as a controlling factor. Using the SUR methodology, they report the following estimated equation[7]

$$\Delta y_{it} = \underset{(-2.26)}{-0.024} \times assassinations_{it} + other\ covariates$$

Their findings indicate one additional (average per capita) political assassination during a decade results in a fall of the average growth rate over a decade by 2.4 percentage points.

5.2 The fixed-effects dummy-variable approach

The fixed-effect dummy-variable approach assumes that the time and country unobserved effects, α_t and γ_i, are fixed and uses period and country specific dummy variables. This is by far the most popular method used in the literature. Some applications of this methodology for the estimation of the effects of war and terrorism on growth follow.

Collier (1999) presents evidence on the effect of civil wars on the rate of growth using a sample of 78 countries over the three decades 1960-1989 (three time units, one for each decade). He found a negative and significant effect of civil war on economic growth. He reports the following fixed-effect estimates

$$\Delta y_{it} = \underset{(-2.34)}{-0.00020} W_{it} + other\ covariates$$

where Δy_{it} is country i's average annual per capita GDP growth rate in decade t and W_{it} is the number of months with civil war in country i during decade t. The coefficient on W_{it} gives us

[7] In fact, Easterly and Levine use the average number of political assassinations per thousand population over a decade and get an estimate equal to -23.78.

the marginal effect of an additional month of civil war on the decade-average annual growth rate. Therefore, an entire decade of war (120 months) reduces the average growth in 2.4 per cent points ($0.0002 \times 120 = 0.024$).

Caplan (2002) analyzed the different effects of wars fought at foreign and domestic soil on growth, inflation, public expending, tax revenue and monetary growth. Using a sample of annual data for 66 countries over the 1953-1992 period, he reports the following fixed-effect estimates

$$\Delta y_{it} = \underset{(1.80)}{2.333} FW_{it} - \underset{(2.00)}{2.027} DW_{it} + other\ terms$$

where FW_{it} and DW_{it} are dummy variables defined as equal to one if country i in year t fought a war in foreign and domestic soil respectively and zero otherwise. The coefficient on the foreign war dummy is positive and only significant at the ten per cent level. The coefficient on the domestic war dummy is negative and marginally significant. Since growth rates are measured in percentage points, an additional year of domestic war reduces the growth rate by 2.03 percentage points. In contrast with Collier (1999), Caplan does not control for any covariates but his estimate of the effect of domestic war is very similar to Collier's estimate of the effect of civil war.

Blomberg, Hess and Orphanides (2004) provide evidence on the effect of various forms of conflict on economic growth. They consider terrorism, internal conflict and external conflict. Using an unbalanced sample of 177 countries from 1968 to 2000 they fit the following panel-growth regression

$$\Delta y_{it} = \underset{(-12.002)}{-5.545} y_{it-1} \underset{(-1.773)}{-0.438}\, T_{it} \underset{(-5.226)}{-1.270}\, I_{it} \underset{(-4.458)}{-3.745}\, E_{it} + other\ covariates$$

where Δy_{it} is the rate of growth of per capita GDP for country i in period t, and T_{it}, I_{it} and E_{it} are dummy variables indicating whether in country i in period t there was, respectively, a terrorist incident, internal conflict and external conflict. Terrorism seems to have a lower economic impact than internal conflict which in turn has a lower effect than external conflict and this is in fact what the authors claim. However, multiplying coefficients estimates by the standard deviation of the covariates yields $0.438 \times 0.443 = 0.194$, $1.270 \times 0.355 = 0.451$ and $3.745 \times 0.094 = 0.352$ respectively, showing that the effect of external conflict is in fact lower than the effect of internal conflict. Contrary to Caplan (2002) findings, the effect of external conflict turns out to be negative.[8]

Tavares (2004) also provides evidence on the effect of terrorism on per capita GDP growth. He uses a sample of unspecified countries for the period 1987-2001 and reports the following

[8]Blomberg, Hess and Orphanides' (2004) definition of external conflict includes wars fought on domestic soil against foreign nations, whereas Caplan (2002) would include those as domestic wars.

estimated regression

$$\Delta y_{it} = \underset{(4.80)}{0.261}\Delta y_{it-1} + \underset{(1.20)}{0.017} y_{it} \underset{(-2.89)}{-0.029}\, T_{it} + \underset{(3.15)}{0.121}(T_{it} \times PR_{it}) + other\ covariates$$

where T_{it} is the number of terrorist attacks per 10 million inhabitants, PR_{it} stands for the level of political rights, an index ranging from 0 to 1. According to his results, a one standard deviation increase in the level of terrorism leads to a fall in per capita GDP growth of about 0.17 per cent $(0.029 \times 5.99 = 0.17)$ in a country scoring at lower end of political rights index and to an increase in per capita GDP growth of 0.55 per cent $((-0.029 + 0.121) \times 5.99 = 0.55)$ for a country scoring at the upper end of the political rights index.

Neumayer (2004) estimates the effect of political violence on tourist arrivals using a panel of 194 countries during the period 1977-2000. He reports the following estimates

$$n_{it} = \underset{(3.56)}{0.63} n_{it-1} \underset{(3.51)}{-0.12}\, c_{it} + other\ covariates$$

where n_{it} is the (log of) the number of annual tourist arrivals (overnight visitors) and c_{it} is Uppsala Conflict Data Project armed conflict intensity index. A one standard deviation increase in the conflict index results in a $(0.12 \times 0.82 = 0.0984)$ 9.8 per cent fall in the number of tourists the same year, $(0.0984 \times 0.63 = 0.062)$ a 6.2 per cent fall a year after, and so on.

5.3 The Chamberlain approach

The third approach to estimate the economic cost of conflict using panel data follows a procedure designed by Chamberlain (1982). Instead of assuming that the unobserved effects are fixed or random, Chamberlain suggested that unobserved effects could be linear functions of the covariates, that is, $\gamma_i = \psi + \sum_{t=1}^{T} X_{it}\lambda_t + v_{it}$. Under this assumption and ignoring time effects, equation (6) becomes

$$\Delta y_{it} = \psi + X_{i1}\lambda_1 + \ldots + X_{it}(\beta + \lambda_t) + \ldots + X_{iT}\lambda_T + r_{it}$$

where $r_{it} = \varepsilon_{it} + v_{it}$. For illustration consider the $T = 2$ case where

$$\Delta y_{i1} = \psi + X_{i1}(\beta + \lambda_1) + X_{i2}\lambda_2 + r_{i1},$$

$$\Delta y_{i2} = \psi + X_{i1}\lambda_1 + X_{i2}(\beta + \lambda_2) + r_{i2}.$$

Chamberlain proposes a two-step estimation procedure of the vector of structural parameters $\theta = (\psi, \lambda_1', \lambda_2', \beta')'$. In the first step, the vector of reduced form parameters $\pi = (\psi, \beta' + \lambda_1', \lambda_2', \psi, \lambda_1', \beta' + \lambda_2')'$ are estimated by OLS applied to each equation. In the second step, the structural parameters are estimated by classical minimum distance, that is, minimizing

the quadratic form $(\hat{\pi} - H\theta)'\Xi(\hat{\pi} - H\theta)$, where Ξ is a positive definite matrix and H is a conformable auxiliary matrix with zeros and ones.

Knight, Loayza and Villanueva (1996) applied Chamberlain approach to quantify the effect of wars on ouput per capita growth rates and the investment to GDP ratio using a panel of 79 countries over three five-year periods from 1971 to 1985. They report the following estimates

$$\Delta y_{it} = \underset{(-1.51)}{-0.0132} W_{it} + \underset{(2.92)}{0.0165} \left(\frac{I}{Y}\right)_{it} + other\ covariates$$

$$\left(\frac{I}{Y}\right)_{it} = \underset{(-6.78)}{-1.3232} W_{it} + other\ covariates$$

where W_{it} is the number of war years in a particular five-year interval as a fraction of the total number of years in the sample. They find a negative effect of war on per capita GDP growth and investment to output ratio, although the former is not statistically significant.

Knight, Loayza and Villanueva (1996) acknowledge the existence of a two-channel mechanism through which war affects growth. A direct effect of war captured by the growth equation and an indirect effect through investment. According to their estimates, if the fraction of war years in the sample increases 1.5 additional war years (a ten percent of the number of years in the sample), the total incidence of war cost of conflict would be a reduction of the per capita growth rate in 3.5 percentage points ($(-0.0132 - 0.0165 \times 1.3232) \times 0.1 = -0.035$).

5.4 Gravity equations

Gravity equations are very popular in international trade studies. They are specially designed to fit a special type of three dimensional data arrays. For illustration consider a set of J countries and let x_{ijt} be country i's (log) exports to country j in period t. Thus, for a given time period there are $(J \times (J-1))$ trade flows. A gravity model assumes trade flows are proportional to the countries' income, their distance, and other control variables as given by

$$\ln(x_{ijt}) = \beta_1 \ln(1 + z_{it} z_{jt}) + \beta_2 \ln(y_{it} y_{jt}) + \beta_3 \ln(y_{it} y_{jt} / p_{it} p_{jt}) + \beta_4 \ln(d_{ij}) + other\ covariates$$

where $z_{it}z_{jt}$ is the product of the countries measurements of conflict at time t, $y_{it}y_{jt}$ is the product of countries i and j real GDPs in period t, $p_{it}p_{jt}$ is the product of countries' populations and d_{ij} is the distance between countries.

Nitsch and Schumacher (2004) report evidence for more than 200 countries during the 1968-1979 period on the effect of various forms of conflict on trade. They report an estimate of β_1 equal to -0.041 (t-stat -5.87) when z_{it} is the number of terrorist incidents in country i at period t. Since both trade flows and conflict are measured in logs, coefficients can be interpreted as elasticities. Thus, a 100 percent change in $z_{it}z_{jt}$ resulted in a 4 percent fall in exports.[9] Nitsch

[9]The impact might look like small, but it is large. A 100 percent increase in $z_{it}z_{jt}$ does not require such a

and Schumacher also used the number of political assassinations as a measure of conflict, their estimate of β_1 was in this case -0.160 (t-stat -16.0). Repeating the same exercise with conflict measured as the fraction of the sample period involved in external war, their estimate of β_1 was -0.395 (t-stat -14.1).

Glick and Taylor (2010) used a gravity model to assess the effect of war on trade. They assembled a sample of 172 countries during the 1870-1997 period from various sources and used average exports and imports flows between country pairs. Instead of a continuous measurement of conflict, Glick and Taylor included a dummy variable D_{ijt} equal to one when countries i and j were engaged in war in period t and zero otherwise, as well as up to ten lags of the dummy variable. They report the following fixed effects estimates

$$\ln(x_{ijt}) = \underset{(-8.09)}{-1.78}\, D_{ijt} \underset{(-4.74)}{-1.28}\, D_{ijt-1} \underset{(-6.00)}{-1.32}\, D_{ijt-2} \underset{(-7.47)}{-1.12}\, D_{ijt-3} \underset{(-5.38)}{-0.70}\, D_{ijt-4} \underset{(-6.11)}{-0.55}\, D_{ijt-5}$$

$$\underset{(-4.63)}{-0.37}\, D_{ijt-6} \underset{(-3.14)}{-0.22}\, D_{ijt-7} \underset{(-3.00)}{-0.24}\, D_{ijt-8} \underset{(-1.83)}{-0.11}\, D_{ijt-9} \underset{(-0.50)}{-0.03}\, D_{ijt-10} + other\ covariates$$

There is a clear decaying pattern in coefficient estimates, which are statistically significant up to the eight lag. As trade is measured in logs but war is not, the interpretation of coefficients is more involved. The contemporaneous contribution of the war dummy to (log) trade flows is -1.78 as compared with the contribution of no war, 0. Thus, war reduces trade to eighty three per cent ($e^0 - e^{-1.78} = 0.83$) contemporaneously, and to seventy two percent one year later ($e^0 - e^{-1.28} = 0.72$), and so on.[10]

6 Event studies

A further methodology used in assessing the economic impact of conflict is the event study methodology. Event studies are used to measure the effect on stock prices of certain types of events such as the release of information on profits, dividend payments, corporate debt issuance, investment decisions, etc. This methodology relies on the assumption of efficient markets according to which share prices should reflect all available information, including any economic or social event. Therefore, if conflict affects the economy, then conflict related events should be accompanied by changes in stock prices.

The event study methodology identifies abnormal returns on stock prices as the difference between the actual return and the normal return on a stock. Let P_t be the stock price at time t and $R_t = (P_t - P_{t-1})/P_{t-1}$ its rate of return. Normal returns are computed as the mean daily return on a window of T trading days before each event: if $t = 0$ is the day of the event, the

change in both countries. For instance, if countries i and j experience 5 terrorist attacks, $z_{it}z_{jt} = 25$. Then, an increase to 7 terrorist attacks in both countries (a 40 percent increase) results in, $z_{it}z_{jt} = 49$, almost a 100 percent increase in $z_{it}z_{jt}$.

[10] Because the estimated equation is the conditional mean of the log trade flows, exponentiation does not yield the conditional mean of trade flows. However, it should be taken as an approximation.

normal return is computed as the arithmetic mean of daily returns from $t = -t_1$ to $t = -t_2$. The abnormal return, computed as

$$AR_t = R_t - \frac{1}{T}\sum_{t=-t_1}^{-t_2} R_t$$

is considered the effect of the event on the stock return. In addition to abnormal returns, the event study methodology also relies on accumulated abnormal returns defined as

$$CAR_t = \prod_{i=0}^{I}(1 + AR_{t+i}) - 1$$

where I is the number of periods during which the returns are accumulated. Some applications of this methodology follow.

Chen and Siems (2004) investigated the Dow Jones Industrial index reaction to 14 terrorist and military events. Out of the 14 events analyzed, 12 had a statistically significant abnormal return and the September 11th was the event with the largest abnormal return (-7.14 per cent). Chen and Siems also applied the same methodology to asses the effect of the 9/11 event on 33 stock market indexes from 28 countries, 31 of which exhibited negative and statistically significant abnormal returns.

A more sophisticated way of computing the normal return is the market model of financial economics

$$R_{it} = \beta_i R_{Mt} + u_{it}$$

where R_{it} is the return on stock i on day t in excess over the risk-free rate of return, R_{Mt} is the return on the market portfolio (also measured in excess over the risk free rate of return) and u_{it} is a zero mean disturbance. Identifying the normal return as the systematic part of the previous equation implies that the residuals from this equation are the abnormal returns. The market model is sometimes extended to a three-factor model à la Fama and French (1993, 1996). Using this framework, a few other papers provide evidence in favour of the hypothesis that terrorism and violent conflict affects asset prices negatively, see Chesney and Reshetar (2007), Guidolin and La Ferrara (2005) and Drakos (2004, 2009).

A monetary figure of the impact of terrorism on stock prices is provided by Karolyi and Martell (2005) who find that during the 1995-2002 period, the 75 terrorist attacks against publicly traded US companies had on average a direct impact on the firm's stock rate of return of -0.83 per cent, which amounted to 401 million US dollars in market capitalization.

Conflict does not always have a negative effect on stock prices, Guidolin and La Ferrara (2007) found that the death of the rebel leader and the sudden end of the war in Angola in 2002 resulted in an abnormal return of -0.032 in the portfolio of diamond mining firms holding concessions in Angola. This finding indicates that the war conflict had a positive effect of those stocks. Similarly, Berrebi and Klor (2010) found that terrorism has a 7 percent positive abnormal return in a portfolio of Israeli defence stocks and a negative 5 percent abnormal return

in a portfolio of Israeli non-defence stocks.

7 Natural experiments

In an experiment, the scientist studies the effect of a treatment on a sample of subjects as compared with a control sample of untreated subjects. In a controlled experiment, assignment of subjects to treatment and control groups is random. In social science research, assignment of subjects to treatment or control samples is oftentimes unethical, unlawful or unfeasible. In this cases, scientists resort to quasi-experimental methods, sometimes referred to as observational studies or natural experiments.[11] In a natural experiment, the scientist has no control over the assignment of subjects to treatment and control groups: sometimes subjects select their own treatment, other times their environments impose the treatment upon them. Self-selection into a treatment may generate an important bias in the results. A natural experiment exploits an irrelevant event that results in haphazard assignment of subjects to treatment and control groups. A natural experiment is more informative about a causal effect when the researcher observes a large and clear change in the treatment that affects only a sub-population.

The quasi-experimental methodology has been applied to measure the effect of terrorist conflict on various economic magnitudes. Two examples of this methodology follow. Abadie and Gardeazabal (2003) used the September 18, 1998 - November 28, 1999 cease fire declared by terrorist organization ETA as a natural experiment to asses the effect of terrorism on the stock market valuation of Spanish companies. In experimental terms, the cease fire is the treatment. If the terrorist conflict was perceived to have a negative impact on the Basque economy, Basque stocks (stocks of firms with a significant part of their business in the Basque Country) should have shown a positive performance relative to non-Basque stocks (stocks of firms without a significant part of their business in the Basque Country) as the truce became credible. Similarly, Basque stocks should have performed poorly, relative to non-Basque stocks, at the end of the truce. The portfolio of Basque stocks can be viewed as the treated sample and the portfolio of the non-Basque stocks the control group. Abadie and Gardeazabal reported the following estimated regressions

$$R_{Basque} = \underset{(18.41)}{0.6739} R_{Market} + \underset{(2.33)}{0.0049} D_{Good} - \underset{(-2.13)}{0.0017} D_{Bad} + other\ covariates$$

$$R_{Non-Basque} = \underset{(43.53)}{0.8096} R_{Market} + \underset{(0.56)}{0.0005} D_{Good} + \underset{(0.25)}{0.0001} D_{Bad} + other\ covariates$$

where R_{Basque} and $R_{Non-Basque}$ stand for the return on the Basque and non-Basque portfolios, R_{Market} is the return on the market portfolio and D_{Good} and D_{Bad} are dummy variables that take the value of one during a "Good News" period when the cease-fire became credible and a "Bad News" period when the peace process collapsed. In accordance with the theoretical prediction,

[11] See Rosenbaum (2005).

the dummy variables were significant for the Basque portfolio and not significant for the non-Basque portfolio. Compounding the 0.0044 coefficient on the Good News dummy over the 22 trading sessions of the Good News period yields a compounded abnormal return of 10.14 percent for the Basque portfolio relative to the non-Basque portfolio. Analogous calculations yield a -11.21-percent compounded abnormal return for the Basque portfolio relative to the non-Basque portfolio during the 66 trading sessions of the Bad News period.

Benmelech, Berrebi and Klor (2010) analyzed the cost in terms of employment opportunities and wages of harboring terrorism in Palestinian districts. They used a sample of all 143 suicide attacks in Israel by Palestinians between September 2000 and December 2006. Benmelech, Berrebi and Klor noticed that some of the suicide attack attempts were interrupted by security forces or civilians while others reached their targets. This fact permits an experimental interpretation of their results. The treatment in this case is the "successfulness" of the attacks. The treated sample would be the sample of all the attacks which reached their targets and the untreated sample those attacks interrupted. These authors report the following estimates

$$\Delta u_{it} = \underset{(4.00)}{0.0140} D_{it} + other\ covariates$$

where i indexes the district where the attack originated, Δu_{it} is the change in district i's unemployment rate in the quarter when the attack took place and the following quarter and D_{it} is a dummy variable that takes a value of 1 when the attack reached its target and zero otherwise. Districts where "successful" attacks originated exhibited a 1.4 percentage points higher increase in the unemployment rate.

Randomized experiments have good internal validity, that is, they are good for establishing a causal relationship. Natural experiments, like the ones surveyed here, have less internal validity than randomized experiments. Sometimes nature provides a haphazard treatment assignment, thus providing a fairly high internal validity. External validity, the possibility of generalizing the results of the natural experiment to other populations, might be low particularly when, as in the Basque and Palestinian examples, the analysis corresponds to a specific conflict.

8 Comparative case studies

A case study is a tool in social science research. It is a meticulous study of a single unit. This methodology has also been used to asses the economic cost of conflict in countries or regions under conflict. When analyzing a pool of countries, the resulting estimate of the economic cost of conflict can be interpreted as the average effect. The average impact of conflict surely over estimates the effect for some units and under estimates the effect for others. Case studies have the potential of identifying particularly large or small effects for specific units. In addition, a careful study of a single unit allows the researcher to pay more attention to particular mecha-

nisms that might pass unnoticed in the aggregate. Therefore, the case study methodology stands up as a powerful tool of research. Having the possibility of analyzing a single unit in depth, however, comes at the cost of losing external validity, as the results might be due to specific characteristics of the particular unit being analyzed.

In fact, many of the previously mentioned papers are case studies. There are case studies of the effect of armed conflict in Nicaragua (DiAddario, 1997), Nepal (Kumar, 2003) and Sri Lanka (Arunatilake, Jayasuriya and Kelegama, 2001). Case studies have also been used in order to study the economic effects of terrorism in Israel (Eckstein and Tsiddon, 2004) and Spain (Enders and Sandler, 1991 and 1996). There are also examples of case studies of the economic effect of conflicts in specific sectors such as the effect of the 9/11 terrorist events on airline stocks (Drakos 2004) and Chicago real estate market (Abadie and Dermisi 2008 and Dermisi 2007). The common denominator of these studies is the fact that they concentrate on a single unit. These papers use some of the previously mentioned techniques to asses the economic impact of conflict and therefore will not be reviewed here.

A particular type of case study deserves more attention: the comparative case study. Comparative case studies are often used by researchers to study the effect of events or policy measures on aggregate units such as regions or countries. The goal in these studies is to estimate the evolution of outcomes for a unit affected by an event and compare it with the evolution of a control group. It is often the case that there is not a single control unit with the same characteristics of the unit exposed and therefore a combination of control units is a better comparison group than any single unit. A particular way of carrying out this comparison is the synthetic control method suggested by Abadie and Gardeazabal (2003) and refined by Abadie, Diamond and Hainmueller (2010).

The synthetic control method can be easily described as follows. Let J be the number of available control units and $W = (w_1, ..., w_J)$ a vector of non negative weights which sum to one. Let X_1 be a $(K \times 1)$ vector of pre-conflict values of K relevant characteristics for the treated unit and X_0 be a $(K \times J)$ matrix which contains the values of the same variables for the J possible controls. These K covariates are those factors the researcher believes affect the outcome variable. Let V be a diagonal matrix with non-negative components. The values of the diagonal elements of V reflect the relative importance of the different covariates. The vector of weights W^* is chosen to minimize $(X_1 - X_0W)'V(X_1 - X_0W)$ subject to $w_j \geq 0$ $(j = 1, 2, ..., J)$ and $w_1 + ... + w_J = 1$. The weights chosen in this manner define a synthetic control unit with covariate values X_0W^*, a linear combination of the potential control units characteristics. Once the match between the treated unit and the synthetic control is done, it remains to compute the counterfactual value of the outcome variable during the post-treatment period. Let Y_1 be a $(T \times 1)$ vector whose elements are measurements of the outcome variable for the treated unit during the post-treatment period. Similarly, let Y_0 be a $(T \times J)$ matrix which contains the values of the same variables for the control units. The counterfactual values of the outcome is computed as $Y_1^* = Y_0W^*$. The difference between the actual and counterfactual values of the

outcome is $Y_1 - Y_1^*$.

Abadie and Gardeazabal (2003) used this procedure to estimate the economic impact of terrorism in the Basque Country economy. Using the synthetic control method, Abadie and Gardeazabal formed a comparison group as a combination of other Spanish regions that was "similar" in various economic dimensions (thought to be potential growth determinants) to the Basque Country economy in the period prior to the uprising of terrorism. The output gap between the actual and counterfactual values yielded a 10 percent annual per capita GDP loss over a 20-year period, a sizable output loss.

The synthetic control method allows the researcher to conduct placebo analysis by applying the same procedure to an untreated subject. Abadie and Gardeazabal applied the same procedure to another Spanish region, Catalonia, not directly affected by a terrorist conflict. The placebo comparison for Catalonia displayed a very small output gap. Furthermore, conducting the placebo study on all untreated subjects yields an empirical distribution of outcome gap (the difference between the outcome of the treated and its synthetic control). This empirical distribution can be used to assess the statistical significance of the outcome gap for the treated. This method is specially suited for a single unit analysis. However, the method is potentially useful for application to multiple units, although there is no guarantee that a good match can be found for all units.

9 Discussion

This paper reviews the methods for assessing the economic cost of conflict and illustrates them with a selective collection of examples. Overall, the literature reviewed shows that conflict exerts significant economic costs. Since conflict is a latent variable for which only proxy measurements are available, classical error-in-variables econometrics suggests that regression estimates of the effect of conflict should be downward biased, assuming errors of measurement are uncorrelated with the latent variable.

After reviewing the literature, we believe there are several issues that deserve further attention. First, the papers reviewed offer a wide range of estimates from low to high quantities. This is particularly true for the panel data evidence reported above. There are several reasons for this heterogeneity of results. First, not all types of conflict have the same economic cost. Political instability, terrorism and war have very different economic impacts. A second source of variation accrues from the different samples (units and periods) and methods used by researchers. Therefore, the findings of several independent studies need to be integrated. Even though a meta-analysis seems rather difficult to carry out, some extra effort in this direction is needed.

Second, the empirical evidence reviewed in this survey focuses primarily on establishing a causal link between conflict and some economic magnitude and often little attention is paid to determining the quantitative effect. As argued above, after the causal link is established,

generally by the statistical significance of a parameter estimate, researchers sometimes do not take the further step of quantifying the effect. Examples of this practice are most of the cross-section and panel data evidence reviewed. We have sometimes been able to take this further and simple step. For instance, in some of the cross-section and panel data items reviewed above, we have been able to quantify the costs by simple arithmetic. These require knowledge of the scale of the conflict measurement which is not always reported.

Third, further research is needed in the area of policy analysis. It would be interesting to estimate the economic cost of policies and the benefits they bring about so that a cost-benefit analysis could be performed. Policy effectiveness and its quantitative assessment, however, remains an unexplored issue.

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