Dustbowls and High Water, the Economic Impact of Natural Disasters in China
Tam Bang Vu and David Hammes

Abstract
This paper investigates the consequences of natural disasters on annual output and output growth over the period 1995 to 2007 in China. Using data on gross regional product values, we follow the Blundell-Bond System GMM procedure to control for the presence of lagged dependent variables. The results show that the impact of number of people killed on annual output and output growth are both negative. However, the impact of the number of people affected and amount of direct damage on annual output differ from those on output growth and are different for different regions.

JEL classification: O40, Q54

Key words: China, natural disasters, annual output, output growth

Introduction
Natural disasters have increasingly taken the front seats in government policy analyses, most recently and urgently in relation to the evident warming of the planet and the attendant changes in the patterns of climatic events predicted to accompany such warming (IPCC, 2007). For example, the United Nations reports: “Since 2000, some 1.6 billion have lost their homes or livelihoods or have suffered other damage; by some measures this constitutes a four-fold annual increase from the decade of the 1970s.”

Research in both the social and natural sciences has been devoted to increasing our ability to predict, prepare for, and mitigate the costs of disasters. Curiously, despite the death, dislocation, and direct damage caused by natural disasters, few economists participate in developing this research agenda. Nor have many attempted to answer the many economically relevant questions relating to natural disasters.

Almost all of the current research on the topic studies disasters ex ante, as is done in the large preparedness literature that aims to describe how societies should better prepare for disasters and reduce their direct damage. In contrast, this paper focuses on the natural disasters’ ex post impact on the macro-economy. It estimates the costs of these events in terms of forgone production, using a regional panel dataset for China. We investigate the determinants of these costs and compare the economic costs of disasters across regions in China.

Our results show that deaths caused by natural disasters reduce both annual output and output growth. However, the impact of the number of people affected and amount of direct damage on annual output differ from those on output growth and are different for different regions.

Section two discusses the existing economic literature and details our goals in this paper. Section three analyzes the data, Section Four methodology, and Section Five the results.
Section six concludes and provides economic implications of the findings.

**Literature review**

**Impacts of disasters on output and output growth:**

One strand of development research examines the ways in which mostly rural households prepare and deal with sudden unexpected income shocks and the households’ ability to insure against them (e.g., Townsend, 1994; Paxson, 1992; and Udry, 1994). A second approach examines specific disaster events - such as hurricane Mitch in Honduras, the Kobe earthquake in Japan - estimating some of the specific costs and consequences of the individual events (e.g., Benson and Clay, 2004; Coffman and Noy, 2009; Halliday, 2006; Horwich, 2000; Narayan, 2001; Selcuk and Yeldan, 2001; and Vos et al., 1999).

China has an elevated exposure to natural disasters, especially storms and droughts. Unlike geo-physical disasters - earthquakes, volcanic eruptions and tidal waves they both may generate – storms and droughts are reasonably frequent and expected, even if their magnitude can sometime be extreme. China’s consistent exposure to these disasters may generate different macroeconomic dynamics when compared to countries that only experience infrequent but potentially very large geo-physical events.

Our work on China’s economic vulnerability to natural disasters differs from existing literature as we avoid the difficulty in identifying the impact of a single event in a case study. Our time-series findings may provide general conclusions which otherwise might only be derived from a meta-analysis relying on a large number of such single-event studies.

Only a few papers examine the macroeconomic facet of natural disasters using a multiple-events framework. Albala-Bertrand (1993), attempts to estimate the macro-aspects of natural disasters. This seminal monograph features an analytical model of disaster occurrence and reaction exploiting data on a set of disaster events: 28 disasters in 26 countries over the period 1960-1979. Based on pre-post statistical analysis, the findings show that disasters are associated with increases in real GDP, capital formation, agricultural and construction outputs, the twin deficits (with the trade deficit increasing sharply) and foreign reserves. The inflation and exchange rates are invariant to natural disasters.

Rasmussen (2004) conducts a similar tabulation of the data for Caribbean Islands. Tol and Leek (1999) survey the literature as far back as the 1960s, and argue that the positive effect on real GDP is consistent with a required increase in the flow of new output to replace destroyed capital stock. They emphasize the incentives for saving for and investing in disaster mitigation and recovery efforts.

Skidmore and Toya (2002) and Noy and Nualsri (2007) examine the long-run impact of natural disasters on economic growth. The former use the frequency of natural disasters for the 1960-1990 period for each country normalized by land size in a cross-sectional dataset while the latter use a panel of country—5-years’ observations as in the extensive literature that followed Barro (1997). Both studies investigate the long-run trends (averaged across countries) in contrast with our aim of describing the short-run dynamics of the macro-economy following disasters for a specific developing country. Long-run analysis raises questions of endogeneity in disaster impact that are, to a large extent, absent in the short-run.

We are aware of only two papers that have attempted to investigate the short-run dynamics of output following disasters in a broad, cross-country dataset, and no papers that have attempted to do that for a specific country using national or sub-national regional/sectoral
data. Raddatz (2007) investigates the external sources of short-run output volatility in low-income developing countries. Using a VAR empirical methodology, the paper analyses the contribution of various external shocks, natural disasters among them, when explaining output fluctuations. Raddatz (2007) concludes that natural disasters have an adverse short-run impact on output dynamics.³

Noy (2009) also finds an adverse short-run effect and describes some of the structural and institutional details that worsen the negative impact. In particular, he finds that countries with higher literacy rates, better institutions, higher per capita income, higher degree of openness to trade, higher levels of government spending, more foreign exchange reserves, and higher levels of domestic credit (but with less-open capital accounts) are better able to withstand the initial disaster shock and dampen economic after-shocks.

Given these findings, China is an especially interesting case given its low per capita income yet high literacy rate, rapidly increasing trade openness, and a high degree of government economic involvement. Our paper, based on regional China data enables us to examine some of these suggested links based on the observed differences between regions in their degree of educational attainment, infrastructure, trade, etc.

Several other papers investigate the institutional and structural determinants of the initial disaster costs (Anbarci et al., 2005; Kahn, 2004; Raschky, 2008; and Skidmore and Toya, 2007) or of the subsequent impact on the economy (Noy, 2009 and Cavallo and Noy, 2009). To the best of our knowledge, no work addresses any of these issues using data from the subnational level or with a focus on a particular country.

**Other macroeconomic impacts of disasters**

On the expenditure side, public disaster reconstruction costs may differ more than the original magnitude of destruction of capital that occurred (see Fengler et al., 2008 for more detail). On the other side of the fiscal ledger, the impact of disasters on tax and other revenue sources, has rarely been examined quantitatively. A cross-country investigation of these effects, as in Noy and Nualsri (2008) yields some predictions, but to a large extent, the disaster impacts on revenue and spending depend on the country-specific macroeconomic dynamics occurring following the disaster shock, the structure of revenue sources (income taxes, consumption taxes, custom duties, etc.) and pre-existing large expenditure projects.

Better cost-benefit evaluation of mitigation programs should follow from accurate estimates of the likely fiscal costs of a disaster. These should also assist foreign aid organizations and international multilateral institutions in planning and preparing their programs.

Insurance provides yet another motivation to better estimate the fiscal cost enabling governments to spread the risk of expected disaster losses; directly, through public precautionary saving programs and indirectly through issuing catastrophic (CAT) bonds. Belize provides the only country-specific case of which we know estimating the likely fiscal insurance needs of a government (Borensztein et al., 2008); though whether these estimates for Belize apply to other countries, Vietnam, for example, is an unexplored question.

**Data Collection**

The EMDAT database provides data on natural disasters and their impacts for thirty provinces and regions in China for the period from 1990 to 2009. However, data on regional output values are only available for the period from 1995 to 2007. Hence, this is our estimation period.
As in Noy (2009) and Noy and Vu (2010), we use three reported measures of the magnitude of the disaster to form the damage measures ($DM$): (1) the number of people killed ($KIL$); (2) the number of people affected ($AFF$); and (3) the amount of direct damage ($DAM$). We weigh our measure based on the month in which the disaster occurred. The disaster measures ($DMS$) are calculated based on the cost measure ($DM$) and the onset month ($OM$):

$$DMS = DM(12 - OM) / 12$$ (1)

Data for $KIL$ and $AFF$ are then divided by the provincial population to obtain per capita measures, $KILP$ and $AFFP$. Data for $DAM$ are divided by provincial output values to obtain the ratio of damage to output, $DAMO$.

Provincial data for other variables, including gross regional product values, school enrollments as a proxy for education, domestic trade, freight traffic as a proxy for infrastructure, and numbers of medical staff as a proxy for health care are available from the China’s Statistical Yearbooks (CSY) for the relevant years. The gross regional product values are in constant 100 million Yuan. The domestic trade values are in current 100 million Yuan converted to constant Yuan using the gross regional product deflators.

The education proxy per region is the sum of primary, secondary, vocational, technical school, and college enrollments divided by population. The number of medical staff divided by population provides the proxy for available health care. Data on domestic trade are divided by total output values and are expressed as a percentage of output. The proxy for infrastructure is given by freight traffic divided by population.

**Methodology**

We estimate the equation

$$Y_{it} = \alpha_i^{t} + \alpha_t^{i} + \beta Y_{i,t-1} + \gamma DMS_{it} + \phi X_{i,t-1} + \epsilon_{i,t}$$ (2)

where $Y$ is alternatively annual output or the annual output growth rate, $i$ is a provincial index, and $t$ the time index $\alpha_i^{t}$ and $\alpha_t^{i}$ are the region and time fixed-effects, $DMS_{it}$ is our measure for disaster magnitude, estimated separately for each type of damage (either $KILP$, $AFFP$, or $DAMO$), and $X_{i,t-1}$ are the lagged control variables as described in the previous section.

To control for the presence of lagged dependent variables in the model we employ the Blundell-Bond System GMM procedure as described in Blundell and Bond (1998) and Bond (2002). The Blundell-Bond procedure is a refined application of the Arellano and Bond (1991) and the Arellano and Bover (1995) procedures. Arellano and Bond (1991) developed the difference GMM estimator for dynamic panels. The method accounts for lagged dependent variables that are predetermined but not exogenous: they are independent of current disturbances but may be influenced by past ones. Differencing the lagged dependent variables or taking deviations from the mean will eliminate the fixed effects. Nonetheless, the difference GMM produces biased coefficient estimates and unreliable tests when an endogenous variable is close to a random walk. In this case, past values provide little information about future changes, so the untransformed lags are weak instruments for transformed variables.

To solve this problem, Blundell and Bond (1998) develop a modified procedure introduced in Arellano and Bover (1995). In this approach, they add the difference of the instrumental variable (IVs) to make them exogenous to the fixed effects. In order to build this while retaining the original Arellano-Bonds for the transformed equation, they design a system GMM estimator while left-multiplying the original data by a transformation matrix,
where $Z^*$ is the differenced matrix. Hence for individual $i$, the new data set is

$$X_i^* = \begin{bmatrix} X_i^* \\ Y_i^* \end{bmatrix} = \begin{bmatrix} X_i \\ Y_i \end{bmatrix}$$

When an endogenous variable is close to a random walk, past changes are more predictive of current levels than past levels are of current changes, so the new instruments add extra controls to the original ones for models with lagged dependent variables. Hence, the Blundell-Bond (1998) approach effectively controls for autocorrelation and heteroskedasticity, provides consistent coefficient estimates, and performs more reliable Arellano-Bond tests for autocorrelations and Sargent tests for over-identifying restrictions than the original Arellano-Bond (1991).

We employ the two-step estimation procedure for small samples. For the number of lags to include, we use the Akaike (1973) Information Criterion (AIC) and Schwarz (1978) Bayesian Information Criterion (BIC); for both, only the first lagged value of each variable is significant. We also carry out the modified Hausman endogeneity test to pinpoint the endogenous variables that need instrumental variables in the procedure for each regression.

We use the system-GMM methodology to overcome the problems posed by the inclusion of a lagged dependent variable in a panel setup with some endogeneity. Yet, in order to derive causal inferences on the effect of the disaster variables on our macroeconomic measures of interest (mainly real GDP growth), we generally require further assumptions.

We see no a priori reason to argue that these disaster measures will face any reverse causality from the output growth variable (i.e., growth will Granger cause future disasters); we thus assume (weak) exogeneity of the disaster measures. This assumption is also adopted by the four other papers that use a disaster measure as an independent variable, albeit in very different specifications (Noy, 2009; Raddatz, 2007; Ramcharan, 2007; and Skidmore and Toya, 2002).

Results

Table 1 shows regression results for the model with annual output as the dependent variable where its first lagged value is denoted $OUTL$, together with current and lagged (suffix $L$) values of the other variables. Since we use lagged variables, a special interpretation is needed: in the long run equilibrium,

$$\beta_1 DMS + \beta_2 DMS = (\beta_1 + \beta_2) DMS$$

Hence, we sum up the two coefficients of each variable to obtain a composite coefficient and perform a test on the significance of this composite coefficient. The results of the original coefficient estimates for $KILP, AFFP$, and $DAMO$, are reported in Columns (1.1a), (1.2a), and (1.3a) respectively, whereas the sums of the two coefficients for each variable $KILP, AFFP$, and $DAMO$ are reported in Columns (1.1b), (1.2b), and (1.3b), respectively.

From this table, the impacts of the number of people killed ($KILP$) and the amount of direct damages ($DAMO$) on annual output are negative whereas the impact of the number of people affected ($AFFP$) on annual output is not statistically significant. Specifically, for one percent rise in the ratio of people killed to population, there is a fall of output by 46.99 billion Yuan. Concerning direct damages, its rise by one percent decreases output by 3.27 million Yuan.

For the model with annual output growth as the dependent variable, we first regress annual output growth on each of the variable for disaster damage: $KILP, AFFP, DAMO$, education,
trade, and infrastructure. Table 2 reports the results. It shows that the impact of the number of people killed and the number of people affected on annual output growth are not statistically significant. Nevertheless, the impact of the amount of direct damage is positive and significant: for one percent rise in direct damages, there is a fall of output growth by .235%.

Since many growth models add the initial output value as an independent variable, we also repeat the exercise for the model in Table 1 with initial output values added. Table 3 reports the results. The signs, significances, and sizes of the disaster damages on output growth rates are similar to those in Table 2.

**Conclusion**

China’s consistent exposure to disasters may generate different macroeconomic dynamics surrounding them when compared to countries that only experience infrequent but very large mostly geo-physical events.

In this paper, we examine consequences of natural disaster on annual output and output growth in China. Using similar econometric model as in Noy (2009) and data for primary and secondary industries in China, we employ the Blundell-Bond System GMM procedure to control for the presence of lagged dependent variable in the model. The results show that the impacts of number of people killed on annual output and output growth are negative in both sectors. However, the impact of the number of people affected and amount of direct damage on annual output are different for different sectors.

It is also interesting to see how disaster affects other variables such as tourism and international trade, which are left for future research.

**Data Appendix**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
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<tr>
<td>DAMO</td>
<td>Damage from disaster as % of output</td>
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<tr>
<td>AFFP</td>
<td>Number of people affected by disaster (% of population)</td>
<td>EM-DAT and CSY</td>
</tr>
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<td>KILP</td>
<td>Number of people killed by disaster (% of population)</td>
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<td>freight traffic as infrastructure (million km per person)</td>
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<td>TRADE</td>
<td>domestic trade (% of output)</td>
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<td>EDUC</td>
<td>School enrollment rate (% of population)</td>
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<td>HEALTH</td>
<td>Health care (number of medical staff per person)</td>
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Table 1. Effects of Disasters on Output
Dependent Variable: Annual Output

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Observations 390
p-value for F-test .000
p-value for AR(1) .545
p-value for AR(2) .579
Chis-Sargan .798
Chi²-Hansen .384

Notes: The associated p-values for coefficients are in parentheses. ***, **, * indicate the significant level at 1, 5, and 10 percent respectively, with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.
Table 2. Effects of Disasters on Output Growth. Model Without Initial Output

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Observations 390 390 390
p-value for F-test .000 .000 .000
p-value for AR(1) .148 .327 .345
p-value for AR(2) .791 .820 .668
Chi²-Sagan test .255 .939 .951
Chi²-Hansen test .437 .328 .741

Notes: The associated p-values for coefficients are in parentheses. ***, **, * indicate the significant level at 1, 5, and 10 percent respectively, with p-values in parentheses. The p-value for AR(1) and p-value for AR(2) are from Arellano-Bond test for AR(1) and AR(2) in first differences and second differences, respectively.
Tam Bang Vu and David Hammes

Table 3. Effects of Disasters on Output Growth. Model with Initial Output
Dependent Variable: Annual Output Growth

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Observations 360 360 360
p-value for F-test .000 .000 .000
p-value for AR(1) .014 .008 .019
p-value for AR(2) .536 .832 .363
Chi²-Sargan test .987 .941 .945
Chi²-Hasen test .713 .628 .608

Notes: The same as in Table 5.
Notes
1. See Schwartz (2006) and the United Nation's Integrated Regional Information Network
2. Skidmore and Toya (2002) and Noy and Nualsri (2008) also reach diametrically opposing
   conclusions with the former identifying expansionary and the latter contractionary disaster
   effects.
3. Yet, Raddatz (2007) concludes that negative external shocks explain only a small fraction of
   the output volatility in a typical low-income country.
4. Results available from the authors upon request.

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