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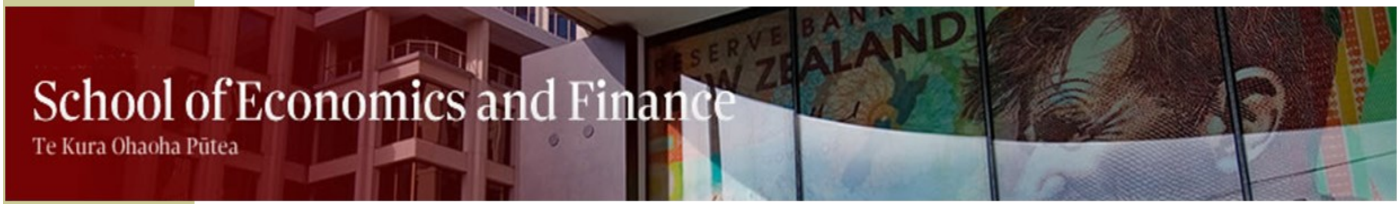

SEF Working paper: 03/2013
June 2013

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Tam Bang Vu and Ilan Noy

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Working Paper 03/2013

ISSN 2230-259X (Print)

ISSN 2230-2603 (Online)

Regional Effects of Natural Disasters in China

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June, 2013

Abstract
We examine the effects of natural disasters on income and investment in China. Using detailed macro-economic province-level data and their history of disaster exposure over the past two decades, and after accounting for two-way causality using a three-stage least-squares estimation procedure, we describe the relationship between disaster mortality and morbidity, disasters' economic damages, government investment and regional economic activity and infrastructure development. The Chinese government's aggressive investment in post-disaster reconstruction is discussed, and the implications of this investment for post-disaster private sector economic activity are analyzed empirically. We further investigate the differential effects of natural disasters on economic activity in the different provinces.

JEL classification: O40, Q54
Key words: China, natural disasters, environment, investment, recovery.

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1. **Introduction**

During the past decade, natural disasters have attracted increasing attention worldwide, maybe especially in East Asia in the wake of several recent catastrophic events; most lethal were the Indian Ocean tsunami in 2004, the Kashmir earthquake in 2005, cyclone Nargis and the Sichuan earthquake both in 2008, and the Tohoku earthquake-tsunami-nuclear triple disaster of 2011).

Furthermore, increased public and policy awareness of this issue is also driven by the growing awareness of global climate change. While the evidence regarding the impact of climate change on trends in disaster occurrence is at best inconclusive, there is little doubt that changing atmospheric conditions and weather patterns will lead to changes in the spatial distribution of disasters, and in particular the emergence of disasters (floods, storms, droughts and extreme temperatures) in areas that were previously considered less vulnerable.

Most of the current research has focused on how to prepare for or mitigate the costs of natural disasters whereas only a handful of papers devote to making assessments of the economic consequences attributed to the disasters and even fewer do it at the sub-national level (which is our focus here).

Natural disasters have recently been especially important for the People's Republic of China (PRC), with the Sichuan (Wenchuan) earthquake of 2008 and its high death toll bringing the issue to the fore. Although earthquakes have typically been associated with the highest mortality in the PRC, storms and droughts occur more frequently than geo-physical disasters, while periodic flooding impacts the most people and property. Besides the obvious importance of the topic for the Chinese economy and its future development, China is also an interesting case given its comparatively low per capita income (typically associated with higher indirect adverse impact) yet very high literacy rates and a high degree of government involvement in investment and infrastructure spending (both typically associated with lower indirect impacts).

We estimate the impacts of natural disasters on Chinese regions and find that disasters seem to be associated with lower per capita income in the short-term but also accompanied by increased investment. Our results on regional estimations suggest that the short-run adverse impact is only present for high-mortality disasters, and there is no evidence that disasters that involve less mortality impose any different impact on these regions. We also find that this adverse impact is more pronounced for the Northeast, the South-Central region, and the Southwest although it is present in all China's regions. Additionally, the Chinese government seems fairly effective at distributing resources across its reach in the aftermath of large natural disasters, and this investment appears to be effective in preventing any further spillovers for the aggregate economy beyond the disaster's immediate aftermath.

2. **Literature review**

The economic literature on natural disasters distinguishes between the direct destructive effects of these events and their indirect impact; with a further distinction for the indirect effects between the short- and the longer-term.[1]

Beyond their natural attributes like the magnitude of the earthquake or the strength of the tropical storm, disasters' direct impacts are a function of the social, economic, cultural and institutional structure of the communities they impact; and their choices regarding prevention, mitigation and preparedness. For example, the Bay of Bengal cyclones Sidr (2007 in Bangladesh) and Nargis (2008 in

[1] Cavallo and Noy (2011) and Kellenberg and Mobarak (2011) provide context and background to these distinctions while Lazzaroni and van Bergeijk (2013) provide a meta-analysis of this research.

Burma) had dramatically different impacts with death tolls of less than 4,000 and more than 135,000 respectively, even though Sidr was a stronger storm.[2]

Thus, attempts to understand the determinants of these direct impacts are important for the social sciences, and are ongoing.[3] In our case, since we focus on natural disasters in a single country, many of these literature's conclusions are less relevant given the homogenous nature of many of these attributes across China's regions. Here, we therefore focus on the aggregate indirect impacts at the regional level.

The direct impacts are only a part of the economic significance of the disasters. In general, we do not understand the indirect impacts as well. The secondary, and potentially more severe, impact of natural disasters is on economic development in the post disaster period. These impacts may result from direct damage to the inputs used in production, to infrastructure, or from the fact that reconstruction and rehabilitation pull resources away from other sectors. Further on in the longer-run, the indirect impacts can manifest themselves in a new equilibrium steady-state in which the economy/society are in a different position to what they were pre-disaster. In contrast to these adverse consequences, reconstruction spending can provide a boost to the domestic economy. Both government funding and privately funded reconstruction from insurance payments, accumulated saving, or from other sources, is bound to provide some temporary stimulus to the local economy, but can also potentially lead to upgraded infrastructure and better long-term outcomes (see Cavallo and Noy, 2011, for a discussion of the evidence).

The literature on the long-term indirect impacts is even more limited, with very few contributions attempting the empirically estimate the dynamic development consequences that disasters entail (e.g., Cavallo et al., 2013, duPont and Noy, 2013, and Lynham et al., 2013). This literature is

[2] Category 5 storm for Sidr and category 4 for Nargis, when measured by the Saffir-Simpson scale.
[3] Example of research that investigate the direct impacts are Kahn (2004) and Raschky (2008).

constrained by the difficulty in identifying precisely long-term effects in economies that are constantly changing in many diverse ways. The difficulty of identifying long-term outcomes is especially relevant to an investigation of China, given its meteoric growth in the past few decades. We therefore restrict our investigation to examining the short-term impact of disasters on China's regions.

The earliest empirical/statistical literature on the short-run effects of natural disasters, in particular the seminal work of Albala-Bertrand (1993), generally identifies evidence for positive impact on GDP but adverse effects on both the government and the trade and current accounts. The basic mechanism that appears to explain this observation is that the destruction reduces the stock of goods available, while it also leads to increased spending on reconstruction (a flow). These arguments fit well within the conventional wisdom that countries/regions recover rapidly from exogenous adverse shocks to the capital stock since the most important asset in most economies is not physical but human capital.[4]

Research in the past decade, however, is less sanguine about the impact of these events, especially in the short-term. This recent research mostly focuses on developing countries, and especially small island states that appear to be especially vulnerable to disasters (e.g., Heger et al., 2008). Noy (2009) finds that the short-run adverse impact of disasters is more significant in smaller economies; but that middle- and low- income countries with a higher literacy rate, better institutions, higher per capita income, higher degree of openness to trade, and higher levels of government spending are in a better position to deal with the initial negative shock and prevent further spillovers into the macro-economy. China would be the poster-child for this ability to deal with disasters given its high literacy, effective

[4] Versions of this observation, that economies recover quickly with a temporary boost to economic activity, can be found much earlier; for example in the seminal books by Adam Smith (1776) and J.S. Mill (1872). Similar observations of a full long-term recovery were also obtained when war damage was analyzed by, for example, Davis and Weinstein (2002).

institutions, openness to trade and an ability to mobilize significant amount of public resources and government spending.[5]

The literature on the regional impacts of natural disasters, even in developed economies is less extensive, and in this case most papers identify some adverse local impact on income (GDP) which may potentially persist for a long time (e.g., Coffman and Noy, 2012; duPont and Noy, 2013; Fisker, 2012; Hornbeck, 2012; and Vigdor, 2008). Hornbeck (2012), for instance, examines US counties several decades after the Dust Bowl of the 1930s and finds that affected counties suffered long-term economic decline that was correlated closely with the extent of the damages to topsoil during the Dust Bowl years.[6]

Noy and Vu (2010) quantify the impact of natural disasters on provinces in Vietnam. They conclude that, in Vietnam, lethal disasters result in lower output growth but those disasters that destroy more property and capital actually appear to boost the economy in the short-run. They also identify different impact magnitudes on different geographical regions and speculate that these differences are related to transfers from the Vietnamese central government. Noy and Vu (2010) is closest to this work in terms of the methodology used.

Here, however, we focus on China, and on an empirical approach and estimation technique that enables us to better estimate the disasters' impacts while emphasizing the regional differences in these impacts.

3. **Data and Methodology**

[5] More recent work that reaches similar conclusions includes Strobl (2012) who uses more detailed measurements for disaster data and a different identification technique and von Peter et al. (2012) who investigate the importance of insurance in ameliorating these adverse dynamics.

[6] A combination of droughts and intensive and inappropriate cultivation in the preceding years led to a loss of much of the fertile topsoil in the Mid-Western High Plains and large scale dust storms that wrecked havoc on people's health and livelihoods.

3.1 Data

Data on natural disasters for 31 provinces and metropolitan centers in China are available from the OFDA/CRED International Disaster database for the period from 1953 to 2011. We use the 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 weighted disaster measure (*DMS*) is calculated based on the damage measure (*DM*) and the onset month (*OM*) to account for the prediction that a disaster earlier in the year will have more of an impact in the same year, but less in the year following, while a disaster that occurred in the latter part of the year will likely affect only the next calendar year's economic activity.[7]

The data for the disaster cost for each province are then divided by the provincial population to obtain per capita measures of disaster costs. When a disaster strikes more than one province, we divide the disaster measures by the sum of the affected provinces' population and enter the result as observations for each province affected by the disaster.[8]

We only focus on sudden-onset events like storms, floods, and earthquakes, since slow-onset events like droughts are much more difficult to precisely measure (both in terms of timing and in terms of costs). Provincial data on other variables for 31 provinces and municipal cities are from the China's Statistical Yearbooks (CSY) published by the National Bureau of Statistics of China (NBSC).[9] Gross regional product, domestic trade, private consumption, government expenditures, and investment values are available in current values of Chinese Renminbi. We convert these data to constant values

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[7] The weighted variables DMS is thus calculated as: $DMS_{i,t} = DM_{i,t} * (12 - OM_{i,t})/12$, and $DMS_{i,t-1} = DM_{i,t} * OM_{i,t}/12$. The subscripts *i* and *t* are for the region and time, respectively; we adopt the same weighting algorithm as Noy (2009).

[8] We resort to this procedure since EMDAT does not provide any information regarding the distribution of damages across the affected provinces in a single event.

[9] Data for Chongqing for 1995-1996 which was then still considered part of Sichuan province is derived from the Sichuan data, by splitting the province's observations using the average share of Chongqing values to Sichuan values for 1997-1999.

using the gross regional product deflators. The exports, imports, foreign direct investment, and other foreign investment values are in current US dollars, and we convert them into constant US dollars using US GDP deflators. We then add up data on primary, secondary, vocational, technical school, and college enrollments to obtain a proxy for regional education. Data on the number of medical staff provides a proxy for available health care. Data on freight traffic and length of highway are used to proxy for infrastructure. All these data are then divided by the population measure to obtain the per capita variables.

Since we speculate that regional differences may matter, we follow the standard division of Chinese provinces into six different regions (see figure 1). Figure 2 describes the evolution of the three impact variables (person killed, person affected, and total damage) over the sample period (1995-2011).

Table 1 describes the number of disaster events in each region, the mean number of events for each province within that region, and a measure of the differences in frequency among provinces within a region (the standard deviation of the number events per province). The least affected regions are the North and Northeast, while the most affected ones are the South-Central and Southwest. Table 2 further described the various types of disasters to affect each region; distinguishing between storms, floods, earthquakes, droughts, and extreme weather (dry/wet and hot/cold). Storms and floods are by far the most common disaster events experiences in all Chinese regions.

Table 3 details the most deadly/damaging events, as it is these extreme events that cause much of the damage. Floods in 1996, 1998, and 2007 were very damaging, as well the Sichuan earthquake of 2008 that was by far the most deadly event in recent history (since the 1976 Tangshan earthquake that was estimated to have killed maybe 250,000 people).

Data on the real interest rate for China are from the International Monetary Fund's *International Financial Statistics*. We generate interaction terms of the interest rate with the regional dummy variables to account for the regional differences in financial markets, the availability of financing, and the role of centrally determined interest rates in the local economy. To account for income convergence, we also include the initial per capita income in our regression specifications. Descriptive statistics—mean and standard deviations—for all the other data used in this paper are included in table 4.

3.2 Methodology

To account for the possible two-way causalities among the variables, we estimate a system of equations:

$$
\begin{aligned}
Y_{i,t} &= \alpha_1 DMS_{i,t} + \alpha_2 DMS_{i,t-1} + \beta X_{i,t} + q_i + s_t + \varepsilon_{i,t} \\
DMS_{i,t} &= \gamma_1 Y_{i,t} + \gamma_2 Y_{i,t-1} + \eta Z_{i,t} + t_i + u_t + \varphi_{i,t} \qquad (1) \\
E_{i,t} &= \kappa_1 DMS_{i,t} + \kappa_2 DMS_{i,t-1} + \mu W_{i,t} + v_i + w_t + \omega_{i,t}
\end{aligned}
$$

Besides the disaster damage variable, *Y* is per capita income, *X* is a vector of the aforementioned control variables, *Z* is a vector of control variables that might affect the frequency and magnitude (cost) of natural disasters in addition to per capita income. *E* is any variable that might be endogenous, and *W* is a vector of variables that affect this endogenous variable. The last three terms are the regional specific disturbance, time specific disturbance, and the idiosyncratic disturbance (*i* and *t*). We employ the Variance Inflation Factor tests (VIF), as in Kennedy (2003), to investigate the possibility of multi colinearity. After removing highly correlated variables, we have system (2), which comprises three equations:

$$
\begin{aligned}
Y_{i,t} = {} & \alpha_1 DMS_{i,t} + \alpha_2 DMS_{i,t-1} + \beta_1 INV_{i,t} + \beta_2 CON_{i,t} + \beta_3 Y_{i,t-1} \\
& + \beta_4 INI_{i,t} + q_i + s_t + \varepsilon_{i,t}
\end{aligned} \qquad (2.1)
$$

$$DMS_{i,t} = \gamma_1 Y_{i,t} + \gamma_2 Y_{i,t-1} + \gamma_3 DMS_{i,t-1} + \eta_1 INFRA_{i,t} + \eta_{21} FDI_{i,t} + t_i + u_t + \varphi_{i,t} \tag{2.2}$$

$$INV_{i,t} = \kappa_1 DMS_{i,t} + \kappa_2 DMS_{i,t-1} + \mu_1 INT_{i,t} + \mu_2 EXPN + \mu_3 DTRA + \mu_4 FOI_{i,t} + v_i + w_t + \omega_{i,t} \tag{2.3}$$

where *INV* is investment, *CON* private consumption ,*INI* initial income per person, *INFRA* infrastructure, *FDI* foreign direct investment, *INT* the real interest rate, *EXPN* the government expenditures, *DTRA* domestic trade, and *FOI* foreign other non-FDI investment such as portfolio investment or foreign loans.

Given the structure of system (2), we estimate this system with fixed effect three stage least squares (FE3SLS) procedure. In contrast to cross sectional estimations, in which finding an instrumental variable (IV) is very difficult, the panel-data estimations enable the use of lagged variables excluded from each equation as IVs. Hence, the reduced form for System (2) is written in System (3) as:

$$DMS_{i,t} = \pi_{11} DMS_{i,t-1} + \pi_{12} DMS_{i,t-2} + \pi_{13} CON_{i,t} + \pi_{14} Y_{i,t-1} + \pi_{15} INI_{i,t} + e_{i,t,1} \tag{3.1}$$

$$Y_{i,t} = \pi_{21} Y_{i,t-1} + \pi_{22} Y_{i,t-2} + \pi_{23} INFRA_{i,t} + \pi_{24} DMS_{i,t-1} + \pi_{25} FDI + e_{i,t,2} \tag{3.2}$$

$$INV_{i,t} = \pi_{31} DMS_{i,t-1} + \pi_{32} INT_{i,t} + \pi_{33} EXPN + \pi_{34} DTRA + \pi_{35} FOI_{i,t} + \omega_{i,t,3} \tag{3.3}$$

Estimating the reduced forms in system (3) using the Blundell-Bond GMM procedure to control for lagged dependent variables, we obtain the predicted values of *DMS, Y,* and *INV* to use as IVs in the FE3SLS estimations for System (2). Not all measures exhibit the complex relationship in System (2). Whenever we find no evidence of two-way causality in an equation, it is dropped. We estimate system

(3) using the Blundell-Bond System GMM procedure as described in Bond (2002). Further discussion of this procedure is available in a methodological appendix.

4 Regression results

We report results for the FE3SLS regression (for system 2) separately for the three different disaster cost measures we have: number of people killed, number affected, and the amount of physical damage. Results are markedly different depending on which disaster measure we use, and we discuss interpretations of these differences below. Results for the aggregate impact of disasters on per capita income and on investment for China are reported in table 5 while results that differentiate between the regional impacts are reported in table 6 for per capita income and table 7 for investment.

When estimating Equation (2.2), the estimated coefficients for $Y_{i,t-1}$ and $Y_{i,t-2}$ are typically not significant; and in these cases we re-estimate the system using only Equations (2.1) and (2.3). As we examine both the immediate impact in the same year, and in the subsequent year to the disaster, we also sum the coefficients for the current measures and lagged values and report them with their associated p-value for the significance of each sum.

In table 5, columns (1)-(2) examine the impact of disasters on per capita GDP and investment (respectively) when disasters' magnitudes are measured by mortality, while column (3)-(4) do the same using the other population proxy—the number of people affected, and columns (5)-(6) use the monetary damage variable as a proxy for disaster magnitude. The most intuitive results are given when disasters are measured by mortality. As previous research has found, the impact of disasters is then negative, on both per capita GDP and investment. In both cases, however, this impact is only statistically distinguishable in the first year; disasters do not seem to have an adverse aggregate impact beyond the first year. It is important to note, though, that even this first-year adverse affect result is remarkable given China's size (both demographic and economic) and the localized nature of disaster events.

Least intuitive is the result we find for the aggregate impact when disasters are measured by the number of people affected. In this case, the impact on both investment and per capita income appears to be positive. This is most likely because floods events are the disaster types that affect by far the most people (and cause relatively less mortality or destruction of property). These can be beneficial to agricultural production (depending on their timing with respect to the crop cycle) and can also generate reconstruction spending fairly rapidly (since they involve less destruction of transportation and similar infrastructure).

The aggregate impact of disasters when these are measured by the amount of physical destruction is not statistically distinguishable for per capita GDP but involves a statistically significant boost to investment as the higher monetary damages generate higher level of investment in reconstruction of infrastructure. Again, these results are informative since they already appear in the immediate year in which the disaster took place, suggesting an ability of the government to start implementing reconstruction infrastructure spending very rapidly.

The results for the additional control variables, as included in table 5 are not very different from results that were previously identified in other literature that examines the determinants of short-term growth. Our main interest in this project, however, is to attempt and identify regional differences in the impact of disasters, as they may be important for practical policy reasons and may also point us to possible explanations for these findings.

We generate regional dummies for the Northeast, East, South-Central, Southwest, and Northwest, leaving the North Region as the reference group. In tables 6-7, we show the regional impact of disasters on per capita income (table 6) and investment (table 7). The other independent variables that are includes in the specifications described in table 5 are also included in these specifications, but are not shown because of space constraints.

As before, we examine the impact of disasters when they are measured by mortality, people affected, and physical damages separately. The odd-numbered columns shows the comparative value of each dummy to the base-dummy (North region); while the even-numbered column reports the absolute value (the magnitude) of each measure by summing the comparative value with the base value.

High mortality disasters appear to have the most intense impact on economic activity (per capita income) in the Northeast, followed by the South-Central region – table 6, columns (1)-(2). This result corresponds well with the cross-country literature that finds more adverse effects for poorer countries and our previous work on different regional impacts in Vietnam (Noy and Vu, 2010). These regions are poorer and less connected to the central government in Beijing than the North and Eastern regions, that are the most prosperous and well connected.[10]

When disaster magnitudes are measured by how many people were affected, the impact on per capita income does not appear to be different across China's regions. In all cases we still obtain the positive conclusion that in the short-term it appears that when disasters are not accompanied by high mortality (but rather by how many people are affected or by the extent of monetary damages) they seem to have a benign effect on per capita incomes across all regions.

The results we obtain for investment are not very different from the results for per capita incomes. Again, the odd-numbered columns show the comparative value to the base-dummy, while the even-

[10] The Southwest and Northwest are even poorer, but these regions have more central government connection given the 'autonomous' status of some of the provinces within these regions—especially Xizang (Tibet) and Xinjiang, the political circumstances associated with that status, and the prevalence of investment in natural resource extraction in these areas.

numbered column reports the magnitude of each measure by summing the comparative value with the base value (and calculating the relevant goodness-of-fit statistic).

In table 7, columns (1)-(2), we see that once again the Northeast is especially vulnerable to the economic indirect impact of disasters (when these are measured by the mortality they cause), in this case it is the impact on investment. In contrast with table 6, the second region that seems especially vulnerable is the Southwest, and not South-Central. The east, the richest region in China, always appears to be the least vulnerable to the economic aftermath of large natural disasters. When disasters are measured by the number of people affected or by monetary damages, there are, once again, no economically meaningful differences across China's provinces.

In an earlier paper on Vietnam (Noy and Vu, 2010), we concluded that the regional effects might imply that the willingness of the central government to provide resources post-disaster across the provinces seems not have been distributed equally. In the case of China, the evidence to this differential funding of reconstruction seem to be significantly weaker, though the evidence does provide some indication that regions that are less close to the central government (located in the Northern region), or are less prosperous, appear to be affected more adversely in the aftermath of catastrophic events. We emphasize, however, that this conclusion is not very robust, given the fact that when disasters are measured by alternative measures of strength, we find no evidence of this differential impact across the various regions.

5 Conclusion

Natural disasters have recently been important for the PRC, with the Sichuan earthquake of 2008 and its high death toll bringing the issue to the fore. We indeed find evidence that these events are not only important because of their immediate, lamentable, and irreversible impact on human populations, but also because they appear to be an impediment to economic development. In China, disasters are associated with lower per capita income in the short-term after relevant events, though with increased investment (most likely associated with reconstruction and replacement of damaged infrastructure).

The Chinese government's aggressive investment in reconstruction after the 2008 earthquake is well-known, but the evidence suggests that this investment is not unusual, and that by increased spending on reconstruction the government is able to prevent further deterioration in per capita incomes beyond the immediate aftermath of a disaster (the immediate first year).

We also estimate the impacts of natural disasters on Chinese regions. Our results suggest that while the adverse short-run impact is present in all China's regions, it is especially pronounced for the Northeast, the South-Central region, and the Southwest. We also find that this differential adverse impact is only present for high-mortality disasters, and there is no evidence that disasters that involve less mortality (but maybe more people affected or more capital damaged) impose any different impact on these regions. The Chinese government appears to be fairly effective at distributing resources across its reach in the aftermath of large natural disasters.

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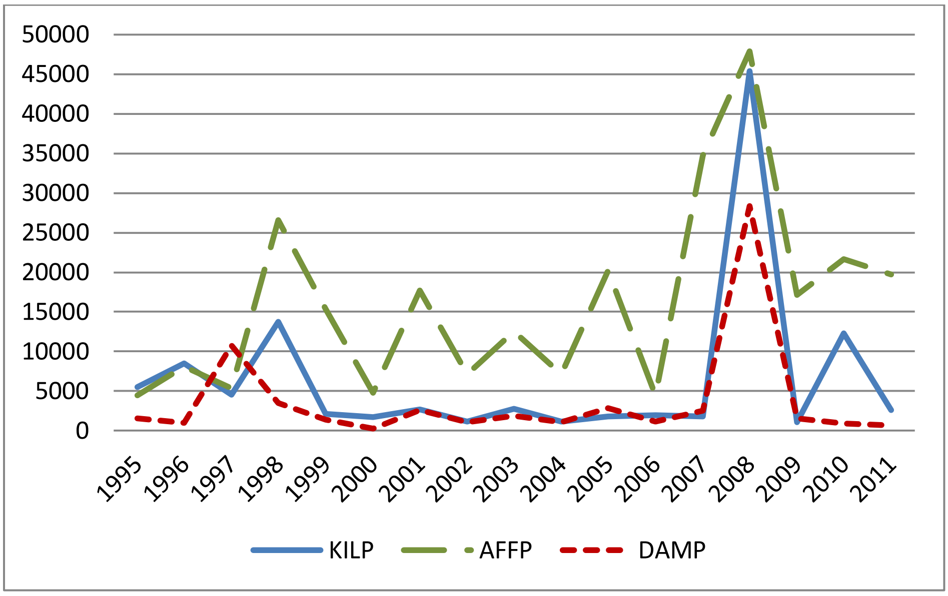
Figure 1. Map of Six Administrative Regions in China

Source: http://www.google.chinatouristmaps.com

Figure 2. Graph of the Three Disasters Measures over Time



Note: KILP: total numbers of killed in persons per 10,000 people.
AFFP: numbers of affected in persons per capita.
DAMP total damage costs in thousands US Dollars per capita.

Table 1. Frequency of Disasters in China's Six Regions: 1995-2011

Region	Numbers	Mean	Standard Deviation
North China	46	2.71	13.13
Northeast China	20	1.18	5.92
East China	100	5.88	29.01
South Central China	137	8.06	39.69
Southwest China	147	8.65	42.58
Northwest China	72	4.24	20.93

Table 2. Disaster Types in China's Six Regions for the Period of 1995-2011

Region	Storm	Flood	Earthquake	Drought	Extreme Weather[a]	Other[b]
North	13	10	7	6	8	2
Northeast	3	10	3	2	1	1
East	42	49	1	3	3	2
South Central	55	60	1	4	7	10
Southwest	18	52	25	6	20	23
Northwest	13	25	12	2	7	8
Total	114	166	42	20	43	36

Note: there were 101 disasters that affected more than one region, so the total of disasters for each type is smaller than the sum of the values for the six regions.

[a] Extreme Weather: consists of extreme dry/wet movement and extreme hot/cold temperature.

[b] Other: consists of epidemic, wildfire, and insect infestation.

Table 3. Three Largest Natural Disasters in Each Category: 1995-2011

Disaster	Region	Year	KIL (#)	AFF (#)	DAM ('000 US$)
By population killed					
Earthquake	Sichuan	2008	87,476	45,976,596	85,000,000
Flood	South	1998	3,656	238,973,000	30,000,000
Flood	North, East, South	1996	2,775	154,634,000	12,600,000
By population affected					

Flood	South	1998	3,656	238,973,000	30,000,000	
Flood	East, South	1996	2,775	154,634,000	12,600,000	
Flood	East, South	2007	535	105,004,000	4,425,655	
By monetary cost of damages						
Earthquake	Sichuan	2008	87,476	45,976,596	85,000,000	
Flood	South	1998	3,656	238,973,000	30,000,000	
Extr. Cold	East, South	2008	129	77,000,000	21,100,000	Temperature

Table 4. Descriptive Statistics for Other Data: 1995-2011

Variable	Total	Mean	Standard Deviation
Per Capita Income (Yuan)	8,283,334	15,717	14,599
Domestic Trade (100 mill.Yuan)	1,162,007	68,353	27,339
Government Exp. (100 mill.Yuan)	620,108	36,476	31,020
Exports (USD 100 mill)	$5.47*10^8$	32,153,244	28,105,000
Imports (USD100 mill)	$4.87*10^8$	28,639,593	24,932,390
Utilized FDI (USD100 mill)	11,745	978	533
Utilized FOI (USD 100 mill)	367	30	21
Consumption (100mill.Yuan)	1,630,339	95,896	34,156
Investment (100 mill.Yuan)	1,684,649	99,097	38,855
Freight Traffic (ton*km)	494,605	29,094	14,872
Highway Length (km)	23,677,017	1,392,766	283
Real Interest Rate (%)	-	2.7	2.9
Medical Personnel (persons)	118,844,660	6,990,862	645,652
Education (enrollment)	$0.77*10^8$	51,582,317	2,041,688

Note: Total is the sum of all values over the period 1995-2011. Mean is the average value per year. FDI and FOI data are only available for 1995-2006.

Table 5. Aggregate Effects of Disasters on GDP Per Capita and Investment

Dep. variable:	Per capita Income	Investment	Per capita Income	Investment	Per capita Income	Investment
Damage variable:	Killed		Affected		Physical Damage	
	1	2	3	4	5	6
$Damage_t$	-4.415** (0.04)	-6.132*** (0.00)	.4069*** (0.00)	.1888*** (0.00)	-.0010 (0.25)	.2241*** (0.00)
$Damage_{t-1}$	.9559 (0.20)	2.658 (0.81)	-.1294 (0.33)	-.0007 (0.33)	.2909* (0.05)	-.0009 (0.37)
SUM of damage variables	-3.459** (0.05)	-3.474** (0.04)	.2775** (0 .05)	.1881** (0.04)	.2899* (0.09)	.2232* (0 .04)
Y_{t-1}	1.036*** (0.00)		1.047*** (0.00)		1.0437*** (0.000)	
INV	0.056*** (0.00)		.0387** (0.05)		.0591*** (0.00)	
CON	0.201*** (0.00)		.2252*** (0.01)		.1940*** (0.01)	
INI	0.180*** (0.00)		.1905** (0.04)		.1836*** (0.00)	
DTRA		0.837*** (0.00)		1.007*** (0.00)		.8577*** (0.00)
EXPN		0.009*** (0.00)		.0072*** (0.00)		.0135*** (0.01)
FOI		.7263 (0.11)		.8096 (0.26)		.4229 (0.24)
INT		-.0158** (0.01)		-.0145** (0.02)		-.0152** (0.02)
p-value F-test	.000		.000		.000	
p-value AR(1)	.324		.514		.465	
p-value for AR(2)	.526		.435		.398	
Chi^2-Sargan test	.612		.398		.534	
Chi^2-Hasen test	.517		.634		.467	

Note:The p-values for coefficients equal to zero (no effect) are provided in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance, respectively. The p-values for AR(1) and AR(2) are from Arellano-Bond test in first differences and second differences, respectively. Sample size is 434.

Table 6. Regional Effects of Disasters on Per Capita Income

Damage variable:	Killed		Affected		Physical Damage	
	1	2	3	4	5	6
	Comp. value	Cumulative value	Comp. value	Cumulative value	Comp. value	Cumulative value
North	-1.42** (0.04)	-1.42** (0.04)	0.44** (0.05)	0.44** (0.05)	.1303** (0.04)	.1303** (0.04)
Northeast	-2.26** (0.05)	-3.68** (0.01)	0.00 (0.17)	0.44** (0.05)	-.0014 (0.38)	.1303** (0.04)
East	-0.27 (0.23)	-1.42** (0.04)	0.00 (0.59)	0.44** (0.05)	0.01 (0.16)	.1303** (0.04)
South Central	-1.05*** (0.01)	-2.48*** (0.01)	-0.01*** (0.01)	0.43*** (0.01)	0.00 (0.61)	.1303** (0.04)
Southwest	-0.13** (0.04)	-1.55** (0.05)	-0.05** (0.02)	0.40** (0.04)	0.00 (0.75)	.1303** (0.04)
Northwest	-0.14 (0.61)	-1.42** (0.04)	0.00 (0.39)	0.44** (0.05)	0.00 (0.37)	.1303** (0.04)
p-value F-test	0.00		0.00		0.00	
p-value AR(1)	0.36		0.83		0.49	
p-value for AR(2)	0.49		0.59		0.69	
Chi^2-Sargan test	0.76		0.70		0.38	
Chi^2-Hasen test	0.93		0.44		0.56	

Note:The p-values for coefficients equal to zero (no effect) are provided in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance, respectively. The p-values for AR(1) and AR(2) are from Arellano-Bond test in first differences and second differences, respectively. Sample size is 434.

Table 7. Regional Effects of Disasters on Investment

Damage variable:	Killed		Affected		Physical Damage	
	1	2	3	4	5	6
	Comp. value	Cumulative value	Comp. value	Cumulative value	Comp. value	Cumulative value
North	-3.87* (0.09)	-3.87* (0.09)	0.51** (0.04)	0.51** (0.04)	0.22*** (0.00)	0.22*** (0.00)
Northeast	-7.99** (0.02)	-11.87** (0.03)	0.22*** (0.00)	0.74*** (0.00)	0.00 (0.15)	0.22*** (0.00)
East	3.06** (0.05)	-0.81** (0.03)	0.00 (0.32)	0.51** (0.04)	0.00 (0.47)	0.22*** (0.00)
South Central	3.61** (0.01)	-0.26** (0.03)	-0.02** (0.01)	0.49** (0.03)	0.00 (0.52)	0.22*** (0.00)
Southwest	-16.15** (0.05)	-20.02** (0.05)	-0.08** (0.05)	0.43** (0.04)	0.00 (0.62)	0.22*** (0.00)
Northwest	-0.25 (0.46)	-3.87* (0.09)	0.00 (0.55)	0.51** (0.04)	0.00 (0.71)	0.22*** (0.00)
p-value F-test	0.00		0.00		0.00	
p-value AR(1)	0.36		0.83		0.49	
p-value for AR(2)	0.49		0.59		0.69	
Chi^2-Sargan test	0.76		0.70		0.38	
Chi^2-Hasen test	0.93		0.44		0.56	

Note:The p-values for coefficients equal to zero (no effect) are provided in parentheses. *, **, and *** denote 10%, 5%, and 1% statistical significance, respectively. The p-values for AR(1) and AR(2) are from Arellano-Bond test in first differences and second differences, respectively. Sample size is 434.

Appendix: Bond (2002) methodology

Bond (2002) is a refined application of the Arellano and Bond (1991) and the Arellano and Bover (1995) procedures. Arellano and Bond (1991) developed the *differenced* 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 differenced 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, $Z_{+}^{*} = \begin{bmatrix} Z^{*} \\ I \end{bmatrix}$, where *Z** is the differenced matrix. Hence for individual i, the new data set is $X_{i+}^{*} = \begin{bmatrix} X_{i}^{*} \\ X_{i} \end{bmatrix}$, $Y_{i+}^{*} = \begin{bmatrix} Y_{i}^{*} \\ Y_{i} \end{bmatrix}$. (3)

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 tests for autocorrelations and Sargent tests for over-identifying restrictions than the original Arellano-Bond (1991). Hence, estimating the reduced forms in System (3) using the Blundell-Bond GMM procedure will sufficiently solve the problem of lagged dependent variables. The predicted values of *DMS, Y,* and *INV* then are used as IVs in the FE3SLS estimations for System (4).