# Regional Effects of Natural Disasters in China: Investing in Post-Disaster Recovery

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## Abstract

We examine the effects of natural disasters on income and investment in China. Using macro-economic province-level data and the provincial history of disaster exposure over the past two decades, 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 China's diverse geographical regions.

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. In Asia, most lethal or costly recent events were the Indian Ocean tsunami in 2004, the Kashmir earthquake in 2005, cyclone Nargis and the Sichuan earthquake in 2008, and the Tohoku earthquake-tsunami-nuclear triple disaster of 2011. Besides increased public awareness, policymaking is also increasingly engaged in disaster risk management (DRM) through the United Nation's sponsored Hyogo Framework for Action and through policy innovations implemented by national and regional DRM bodies.

This growing policy making and public interest is also driven by the growing awareness of climate change. While the evidence regarding the impact of climate change on disaster frequency and intensity 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 facing fewer such risks.

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 their attention to assessing the economic consequences of disasters, and even fewer do it at the sub-national level (which is our focus here).

Natural disasters have recently received more attention in 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 disaster mortality in the PRC, storms and droughts occur more frequently than geo-physical hazards, 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 comparative case. China has a comparatively low per capita income (typically associated with higher adverse impact), yet it also has very high literacy rates and a high degree of government involvement in investment and infrastructure spending (both appear to be associated with lower impacts).

Here, 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 are also accompanied by increased investment. Our results using regional data suggest that the short-run adverse impact we identified is only present for high-mortality disasters and specific regions. There is less evidence that disasters that involve less mortality impose any differential impact across 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 regional reach or 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 between the short- and the longer-term indirect impacts.<sup>1</sup>

<sup>&</sup>lt;sup>1</sup> Cavallo and Noy (2011) and Kellenberg and Mobarak (2011) provide context and background to these distinctions while Lazzaroni and van Bergeijk (2013) provide a preliminary metaanalysis of this research.

Beyond the hazards' 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. These impacts are also determined by communities' choices regarding prevention, mitigation and preparedness. For example, the Bay of Bengal cyclones Sidr (2007 in Bangladesh) and Nargis (2008 in 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.<sup>2</sup>

Thus, attempts to understand the determinants of these direct impacts are important for the social sciences, and are ongoing. This literature focuses mostly on understanding the differences, across countries, in the determinants of direct disaster impacts such as mortality and morbidity. Using a terminology adapted from the World Bank, this literature examines the link between natural hazards and unnatural (social and economic) disasters.<sup>3</sup>

We focus on a single country, China, and many of this literature's findings on the determinants of direct impacts are based on cross-country institutional and

<sup>&</sup>lt;sup>2</sup> Category 5 storm for Sidr and category 4 for Nargis, when measured by the Saffir-Simpson scale.

<sup>&</sup>lt;sup>3</sup> Examples of research that investigate the direct impacts are Kahn (2004) and Raschky (2008).

structural differences. Many of the conclusions from this literature are not directly applicable given the relative homogeneity of many of these attributes across China's regions.

The direct impacts are only a part of the economic significance of the disasters. 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. 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. It can also potentially lead to upgraded infrastructure and better long-term outcomes – a 'built-back-better' scenario.<sup>4</sup>

Further on in the longer-run, the indirect impacts can manifest themselves in a new equilibrium steady state, in which the economy/society is in a different

<sup>&</sup>lt;sup>4</sup> See Cavallo and Noy (2011) and Noy et al. (2014) for discussions of the evidence.

position to what it was pre-disaster. The literature on the long-term indirect impacts is more limited, with few contributions attempting to empirically estimate the dynamic development consequences that disasters entail (e.g., Cavallo et al., 2013, and Hornbeck, 2012). This literature is constrained by the difficulty in identifying precisely long-term effects in economies that are constantly changing. This difficulty is especially relevant to an investigation of China, given its meteoric growth in the past three decades. We restrict our investigation to examining the short-term impact of disasters on China's regions. A longer-horizon investigation of disasters in the Chinese context is indeed desirable but unfeasible with the data and methodology used in this paper.

In due course, an investigation of the long-term impact of the 2008 Wenchuan earthquake should be especially informative of the kinds of longterm post-event dynamics one might encounter in the Chinese context. This investigation will be especially informative about the efficiency of government investment in post-disaster recovery, given the unique arrangements governing this investment in this case.<sup>5</sup>

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.<sup>6</sup>

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 particularly small island states that appear to be

<sup>&</sup>lt;sup>5</sup> Essentially, each unaffected Chinese province was paired to an affected county and required to fund and manage the reconstruction of that county. Thus, there is large diversity in the nature of government intervention across the affected areas.

<sup>&</sup>lt;sup>6</sup> 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).

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. 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 macroeconomy. China could be considered the poster-child for this ability to deal with disasters given its high literacy, effective institutions, openness to trade and an ability to mobilize significant amount of public resources and government spending.<sup>7</sup>

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) that may potentially persist for a long time (e.g., Coffman and Noy, 2012; duPont and Noy, 2013; Fisker, 2012; and Hornbeck, 2012). Hornbeck (2012), for instance, examines US counties several decades after the Dust Bowl of the 1930s and finds that affected

<sup>&</sup>lt;sup>7</sup> More recent work that reaches similar conclusions includes Strobl (2012) who uses more detailed exogenous measurements for disaster magnitudes and a different identification technique and von Peter et al. (2012) who investigate the importance of insurance in ameliorating these adverse dynamics.

counties suffered long-term economic decline that was correlated closely with the extent of the damages to topsoil during the Dust Bowl years.<sup>8</sup>

In Vietnam, Noy and Vu (2010) quantify the macroeconomic impact of natural disasters on provincial economic activity, while Vu and Noy (2013) examine the impact of disasters on firms. 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. Vu and Noy (2013) identify an increase in investment by firms in the aftermath of disasters, but that this increase is, again, concentrated with firms located in the better connected more urban provinces. In this case, then, it seems that even private sector investment is at least partly financed by public resources.

<sup>&</sup>lt;sup>8</sup> A combination of droughts and intensive, extensive, and unsuitable crop 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. Data and Methodology

#### 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.<sup>9</sup>

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

<sup>&</sup>lt;sup>9</sup> 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. This is the same weighting algorithm as in Noy (2009).

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.<sup>10</sup> This procedure probably leads to an under-estimation of the disaster impact on the region that is directly affected. Other research shows that while the directly impacted regions suffer an economic decline, adjacent regions may experience a boom fueled by population movements and reconstruction spending.<sup>11</sup> Our procedure essentially estimates the average impact for the directly impacted and the surrounding area.

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

<sup>&</sup>lt;sup>10</sup> 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. An alternative dataset, DESINVENTAR, does include this breakdown by regions, but is not available for China.
<sup>11</sup> These 'doughnut' effects have been documented in the case of New Orleans after Hurricane Katrina in 2005 (2010) and in Kobe after the 1995 earthquake (duPont et al., 2014 and Chang, 2010).

Statistical Yearbooks published by the National Bureau of Statistics of China.<sup>12</sup> Gross regional product, domestic trade, private consumption, government expenditures, and investment values are available in current values of Chinese Renminbi.<sup>13</sup> We convert these data to constant values 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).

<sup>&</sup>lt;sup>12</sup> Data for Chongqing for 1995-1996 when it was 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.

<sup>&</sup>lt;sup>13</sup> The calendar and fiscal years coincide in China, so we have no reason to transform this data.

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 of 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 in all Chinese regions.

Table 3 details the most deadly/damaging events, as it is these extreme events that cause most 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 is estimated to have killed 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

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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 regional economies. To account for income convergence, we also include the initial per capita income in our regression specifications. All variables are in per-capita terms, except for the real interest rate. Descriptive statistics 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:

$$Y_{i,t} = \alpha_1 DMS_{i,t} + \alpha_2 DMS_{i,t-1} + \beta X_{i,t} + q_i + s_t + \varepsilon_{i,t}$$

$$DMS_{i,t} = \gamma_1 Y_{i,t} + \gamma_2 Y_{i,t-1} + \eta Z_{i,t} + t_i + u_t + \varphi_{i,t}$$
(1)

$$E_{i,t} = \kappa_1 DMS_{i,t} + \kappa_2 DMS_{i,t-1} + \mu W_{i,t} + v_i + w_t + \omega_{i,t}$$

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 (for province *i* and time *t*). We employ the Variance Inflation Factor tests (VIF), as in Kennedy (2003), to investigate the possibility of multicollinearity. After removing highly correlated variables, we have system (2), which comprises three equations:

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

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

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

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

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

$$INV_{i,t} = \pi_{31} DMS_{i,t-1} + \pi_{32} INT_{i,t} + \pi_{33} EXPN + \pi_{34} DTRA + \pi_{35} FOI_{i,t} + \omega_{i,t,3}$$
(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 described in System (2). Whenever we find no evidence of two-way causality in an equation, it is dropped. In particular, when estimating Equation (2.2), the estimated coefficients for  $Y_{i,t-1}$  and  $Y_{i,t-2}$  are typically not significant; and we re-estimate the system using only Equations (2.1) and (2.3).

We estimate the system 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.

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. The first row and the second row of table 5 report the current and the lagged values, respectively, while the third row reports the sum of these two values (the composite effect). For example, the current value in row 1 of column 1 is -4.415 and the lagged value in row 2 of column 1 is 0.9559, so the composite effect of "KILLED" on per capita income is -3.459 (column 1, row 3). This implies that a one percent increase in the ratio of people killed to population is associated with a decrease of per capita income of 4,415 RMB (approximately 10% of China's per capita income). Similarly, the composite effect of "KILLED" on investment is -3.474, implying that one percent increase in the ratio of people killed to population seems to decrease per capita investment by 3,474 RMB per year.

The magnitudes of these estimates can, of course, be considered very high. A per capita income decrease of 10% as a result of a natural disaster would be extremely unusual, as a 1% population mortality rate (of the provincial population) would be much higher than the historical evidence suggests is likely in a Chinese regional disaster. The Wenchuan earthquake of 2008, the deadliest in our dataset though largely an event in a remote area, led to mortality that is about one tenth of that. 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. Even in smaller countries, a localized event such as an earthquake is unlikely to have much national impact.<sup>14</sup> The biggest event in China's recent history, the Wenchuan earthquake of 2008, is also a

<sup>&</sup>lt;sup>14</sup> See Doyle and Noy (2014), and citations therein, for an examination of the New Zealand 2010-2011 earthquakes and a discussion of relative size of disasters and short-term macroeconomic impacts. See also Cavallo et al. (2013) for a comparative evaluation across a dozen case studies.

very localized event affecting a remote rural region in one Chinese province. This earthquake did not cause much impact in the provincial capital, Chengdu, and did not affect any other big city.

Previous research has identified poorer countries, with low human capital, as especially vulnerable to the short-term decline. China, though still having low income compared to the OECD member countries, has very high literacy rates, so the negative direct impact can be viewed as surprising through that lens as well.

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 public 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 infrastructure reconstruction 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 is to 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 the findings we report.

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

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As before, we examine the impact of disasters when they are measured by mortality, people affected, and physical damages separately. The oddnumbered columns shows the comparative value of each dummy to the basedummy (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.

Similarly to the previous table, table 6 row 1 column 1 reports the value for the North, which is -1.42, and row 2 of column 1 reports the value for the Northeast region compared to the North region, which is -2.26. These magnitudes imply a more negative effect on the Northeast region. The cumulative value is in row 2 of column 2 and is -3.68, implying that a one percent increase in the ratio of people killed to population decreases per capita income in the Northeast region by 3,680 RMB. In table 7, the cumulative value for the Northeast in row 2 of column 2 is -11.87, implying that one percent increase in the ratio of people killed to population appears to decrease per capita investment in the Northeast region by 11,870 RMB per year. As we noted earlier, the likely impact is going to be smaller, as the likely magnitude of

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an event is predicted to be significantly smaller than the one percent measure we analyzed here.

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. 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.

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-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. This result, however, is largely dependent on the inclusion of the 2008 Sichuan (Wenchuan) earthquake in our sample. When this event is removed from the dataset (it is clearly an outlier), the coefficient for the Southwest is reduced by about 45%.<sup>15</sup>

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<sup>&</sup>lt;sup>15</sup> We thank a referee for identifying this.

The East, by the far the richest and most urbanized 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.

To summarize, we find is that regions that are more central geographically, more urbanized and richer, or more connected to the central government because of their perceived geo-strategic importance are the ones that experience less indirect adverse impact, and are also the ones that see higher post-event investment. This can partly be explained by the fact that much of this investment is publicly funded. We note that these are speculative conclusions we reach once we identified the regions that are less or more vulnerable. We have no direct evidence that corroborates our conclusions about the determinants of the differences across China's regions.

In order to verify that the weighting scheme we use for the disaster indicators, based on the onset month, does not bias our results, we re-estimate tables 5-7 using the untransformed variables (*DM* instead of *DMS*). The coefficient on GDP in equation (2.2) is still insignificant for all three measures of disaster damages with slightly lower p-values. Thus, we again find no evidence that provincial income (GDP) does have any significant effect on disaster likelihood or immediate impact. Concerning equation (2.1) and (2.3), we find that the results are similar to those in table 5 with slightly different magnitudes and p-values. This finding is also true for tables 6 and 7, implying that the weighted measures do not bias the results very much at the regional level as well. The use of the un-transformed disaster measures appears to change the estimated coefficients by, at most, about 10%.<sup>16</sup>

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 to differ across provinces. In the case of China, the evidence on 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, or are less prosperous, appear to be affected more adversely in

<sup>&</sup>lt;sup>16</sup> These results are available in a web appendix posted on: <u>https://sites.google.com/site/noyeconomics/research/natural-disasters</u>

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. This ability to mobilize resources to more remote and less politically-connected areas was amply demonstrated in the aftermath of the Wenchuan earthquake.

### 5 Conclusion

Natural disasters have recently become more prominent in the People's Republic of China. We indeed find evidence that these events are not only important because of their immediate, terrible, 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 also 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, with less robust adverse finding also for 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 across regions. To summarize, the Chinese government appears to be fairly effective at distributing resources across its extensive reach in the aftermath of large natural disasters and thus mitigating at least some of the indirect adverse impacts.

# References

Albala-Bertrand M J (1993) Natural disaster situations and growth: A macroeconomic model for disaster impacts. World Dev 21(9):1417-1434

Arellano M, Bond S (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev of Econ Stud 58:277–297

Arellano M, Bover O (1995) Another look at the instrumental variables estimation of error-components models. J of Econometrics 68:29–51

Blundell R, Bond S (1998) Initial conditions and moment restrictions in dynamic panel data models. J of Econometrics 87:115–143

Bond S (2002) Dynamic panel data models: A guide to micro data methods and practice. Portuguese Econ J 1(2):141-162.

Cavallo E, Noy I (2011) Natural disasters and the economy – a survey. International Rev of Env and Res Econ 5:63–102

Cavallo E, Galiani S, Noy I, Pantano J (2013) Catastrophic natural disasters and economic growth. Rev of Econ and Stat 95(5):1549-1561

Chang S E (2010) Urban disaster recovery: a measurement framework and its application to the 1995 Kobe earthquake. Disasters 34(2):303-327

Coffman M, Noy I (2012) Hurricane Iniki: Measuring the long-term economic impact of a natural disaster using synthetic control. Env and Dev Econ 17(2):187-205

Doyle L, Noy I (2014) The short-run nationwide macroeconomic effects of the Canterbury earthquakes. New Zealand Econ Papers

duPont W, Noy I (2013) What happened to Kobe? A Reassessment of the impact of the 1995 earthquake. Manuscript

duPont W, Noy I, Okuyama Y, Sawada Y (2014) Long-run consequences of large disasters: the case of the 1995 earthquake in Kobe. Manuscript

Fisker P (2012) Earthquakes and economic growth. INESAD working paper

Heger M, Julca A, Paddison O (2008) Analysing the impact of natural hazards in small economies: The Caribbean case. UNU/WIDER Research Paper #25

Hornbeck R (2012) The enduring impact of the American Dust Bowl: Short- and long-run adjustments to environmental catastrophe. American Econ Rev 102(4):1477–1507

Kahn M E (2004) The death toll from natural disasters: The role of income, geography, and institutions. Rev of Econ and Stat 87(2):271–284

Kellenberg D, Mobarak M (2011) The Economics of natural disasters. Annual Rev of Res Econ 3:297–312

Kennedy P (2003) A guide to econometrics. MIT Press, MA

Lazzaroni S, van Bergeijk P (2013) Natural disasters impact, factors of resilience and development: A meta-analysis of the macroeconomic literature. Institute for Social Studies Working paper

Mill J S (1872) Political economy with some of their applications to social philosophy. Boston: Lee and Shepard

Noy I (2009) The macroeconomic consequences of disasters. J of Dev Econ 88:221-231

Noy I, Seville E, Vargo J (2014) The Economy after an earthquake. Encyclopedia of Earthquake Engineering. Springer.

Noy I, Vu T (2010) The economics of natural disasters in a developing country: The case of Vietnam. J of Asian Econ 21:345-354

Raschky P (2008) Institutions and the losses from natural disasters. Natural Hazards and Earth System Sciences 8:627-634

Smith A (1776) An inquiry into the nature and causes of the wealth of nations. Edwin Cannan, ed. 1904. Retrieved from: <u>http://www.econlib.org/library/Smith/smWN21.html</u>

Strobl E (2012) The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the Central American and Caribbean regions. J of Dev Econ 97(1):131-140

von Peter G, von Dahlen S, Saxena S (2012) Unmitigated disasters? New evidence on the macroeconomic cost of natural catastrophes. BIS working paper #394

Vu T, Noy I (2013). Natural disasters and firms in Vietnam. Manuscript



Figure 1. Map of Six Administrative Regions in China

Source: <u>http://www.google.chinatouristmaps.com</u>



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.

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

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

Region	Storm	Flood	Earthquake	Drought	Extreme Weather <sup>a</sup>	Other <sup>b</sup>
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.

<sup>a</sup> Extreme Weather: consists of extreme dry/wet movement and extreme hot/cold temperature.

<sup>b</sup> Other: consists of epidemic, wildfire, and insect infestation.

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 Temperature	East, South	2008	129	77,000,000	21,100,000		

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

Variable	Total	Mean	Standard Deviation
Per Capita Income (RMB)	8,283,334	15,717	14,599
Domestic Trade (RMB 100 mill)	1,162,007	68,353	27,339
Government Exp. (RMB 100 mill)	620,108	36,476	31,020
Exports (USD 100 mill)	5.47*10 <sup>8</sup>	32,153,244	28,105,000
Imports (USD100 mill)	4.87*10 <sup>8</sup>	28,639,593	24,932,390
Utilized FDI (USD100 mill)	11,745	978	533
Utilized FOI (USD 100 mill)	367	30	21
Consumption (RMB 100mill)	1,630,33995,896	34,156	
Investment (RMB 100 mill)	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 <sup>8</sup>	51,582,317	2,041,688

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

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.

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 <sub>t</sub>	-4.415**	-6.132***	.4069***	.1888***	0010	.2241***
-	(0.04)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)
Damage <sub>t-1</sub>	.9559	2.658	1294	0007	.2909*	0009
-	(0.20)	(0.81)	(0.33)	(0.33)	(0.05)	(0.37)
SUM of	-3.459**	-3.474**	.2775**	.1881**	.2899*	.2232*
damage variables	(0.05)	(0.04)	(0 .05)	(0.04)	(0.09)	(0.04)
Y <sub>t-1</sub>	1.036***		1.047***		1.0437***	
	(0.00)		(0.00)		(0.000)	
INV	0.056***		.0387**		.0591***	
	(0.00)		(0.05)		(0.00)	
CON	0.201***		.2252***		.1940***	
	(0.00)		(0.01)		(0.01)	
INI	0.180***		.1905**		.1836***	
	(0.00)		(0.04)		(0.00)	
DTRA		0.837***		1.007***		.8577***
		(0.00)		(0.00)		(0.00)
EXPN		0.009***		.0072***		.0135***
		(0.00)		(0.00)		(0.01)
FOI		.7263		.8096		.4229
		(0.11)		(0.26)		(0.24)
INT		0158**		0145**		0152**
		(0.01)		(0.02)		(0.02)
p-value		000	.000		.000	
F-test	.000					
p-value		324	.514		.465	
AR(1)	.524		.517			
p-value for	526		.435		398	
AR(2)	.320		-+JJ			
Chi²-						
Sargan	.612		.398		.534	
test						
Chi <sup>2</sup> -Hasen	.517		.634		.467	
test						

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

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.

Damage variable:	Killed		Affected		Physical Damage		
	1 2		3	4	5	6	
	Comp.	Cumulative	Comp.	Cumulative	Comp.	Cumulative	
	value	value	value	value	value	value	
North	-1.42**	-1.42**	0.44**	0.44**	.1303**	.1303**	
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	
Northeast	-2.26**	-3.68**	0.00	0.44**	0014	.1303**	
	(0.05)	(0.01)	(0.17)	(0.05)	(0.38)	(0.04)	
East	-0.27	-1.42**	0.00	0.44**	0.01	.1303**	
	(0.23)	(0.04)	(0.59)	(0.05)	(0.16)	(0.04)	
South	-1.05***	-2.48***	-0.01***	0.43***	0.00	.1303**	
Central	(0.01)	(0.01)	(0.01)	(0.01)	(0.61)	(0.04)	
Southwest	-0.13**	-1.55**	-0.05**	0.40**	0.00	.1303**	
	(0.04)	(0.05)	(0.02)	(0.04)	(0.75)	(0.04)	
Northwest	-0.14	-1.42**	0.00	0.44**	0.00	.1303**	
	(0.61)	(0.04)	(0.39)	(0.05)	(0.37)	(0.04)	
p-value	0	.00	0.00		0.00		
F-lest							
AR(1)	0.36		0.83 0.49		9		
p-value for AR(2)	0.49		0.59 0.		0.6	9	
Chi <sup>2</sup> -Sargan					2		
test	0.76		0.70		0.38		
Chi <sup>2</sup> -Hasen	0.93		0.44		0.56		
test			-				

Table 6. Regional Effects of Disasters on Per Capita Income

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.

Damage variable:	Killed		Affected		Physical Damage	
	1	2	3	4	5	6
	Comp.	Cumulative	Comp.	Cumulative	Comp.	Cumulative
	value	value	value	value	value	value
North	-3.87*	-3.87*	0.51**	0.51**	0.22***	0.22***
	(0.09)	(0.09)	(0.04)	(0.04)	(0.00)	(0.00)
Northeast	-7.99**	-11.87**	0.22***	0.74***	0.00	0.22***
	(0.02)	(0.03)	(0.00)	(0.00)	(0.15)	(0.00)
East	3.06**	-0.81**	0.00	0.51**	0.00	0.22***
	(0.05)	(0.03)	(0.32)	(0.04)	(0.47)	(0.00)
South	3.61**	-0.26**	-0.02**	0.49**	0.00	0.22***
Central	(0.01)	(0.03)	(0.01)	(0.03)	(0.52)	(0.00)
Southwest	-16.15**	-20.02**	-0.08**	0.43**	0.00	0.22***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.62)	(0.00)
Northwest	-0.25	-3.87*	0.00	0.51**	0.00	0.22***
	(0.46)	(0.09)	(0.55)	(0.04)	(0.71)	(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 <sup>2</sup> -Sargan test	0.76		0.70		0.38	
Chi <sup>2</sup> -Hasen test	0.93		0.44 0.5		6	

Table 7. Regional Effects of Disasters on Investment

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). 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 (2).