APPENDIX A: Descriptive Statistics on China's Natural Disaster Losses

Due to its unique geographic environment, China is prone to a variety of natural disasters including earthquakes, storms, floods, droughts, landslides and mudflows. To provide some stylized facts about natural disasters in China, we present descriptive statistics using the data from the Emergency Event Database (EM-DAT) maintained by the CRED. The EM-DAT is a global database that reports natural disasters that occurred across the world from 1900 to the present. The database includes multiple types of hazards (e.g., droughts, extreme temperatures, floods, storms, wildfires, earthquakes, and landslides), and documents direct disaster losses using three different measures: (1) the number of people killed, (2) the number of people affected, and (3) the amount of direct monetary damage (in US dollars). The EM-DAT includes a disaster if it meets at least one of the following criteria: (1) ten or more people killed, (2) 100 or more people affected, and (3) the event has triggered the declaration of a state of emergency or a call for international assistance.

Table A1 (panels A and B) reports the frequency and impacts by hazard types. Panel A shows that, during the 1990-2014 period, storms have been the most common disaster in China, accounting for about one-third of all recorded events. Flooding is the second most frequent disaster (32%), followed by earthquakes (18%). Panel B reports the sum of fatalities, affected population, and direct economic damage from different types of natural hazards. The statistics indicate that, among all, earthquakes have caused the most cumulative human losses in China, while flooding was responsible for the largest amount of economic damage and affected population between 1990 and 2014. After flooding, earthquakes and storms are the second and third most destructive natural disasters in terms of direct economic losses. Overall, we show that earthquakes, flooding, and storms are the three dominant disaster types in China. Although our sample only includes major events in the past two decades, the pattern is consistent with the statistics in other studies (e.g., Chen et al. 2013) that focused on longer time series.

Figure A1and A2 indicates the annual total human and economic losses from all recorded natural disasters nationwide, respectively. According to the EM-DAT data, around 5,500 people in China were killed by various types of natural disasters on average each year, and the average annual economic damage is estimated at more than $15 million (at constant 2000 price) during our study period. Both figures show that China suffered the largest disaster losses in 2008 because of the Wenchuan earthquake, which measured at 7.9M and inflicted the southwestern Sichuan province in May.

Table A1. Frequency and Severity of Natural Disasters in China by Hazard Types

Panel A

Disaster type	Frequency	Percentage (%)
Droughts	28	4.53
Earthquakes	111	17.96
Extreme temperature	12	1.94
Floods	195	31.55
Landslides	54	8.74
Mass movement (dry)	6	0.97
Storms	208	33.66

Panel B

Disaster type	Total deaths	Total affected population	Total damage (thousand US dollars, 2000 price)
Droughts	2,134	443,000,000	28,313,291
Earthquakes	92,716	73,890,957	82,847,597
Extreme temperature	377	81,190,002	17,141,513
Floods	28,016	1,829,711,100	189,457,489
Landslide	4,532	2,184,617	1,711,787
Mass movement (dry)	223	5,475	5,912
Storms	9,668	445,948,583	62,323,969

Source: The EM-DAT.

Figure A1. Annual Total Deaths from Natural disasters in China

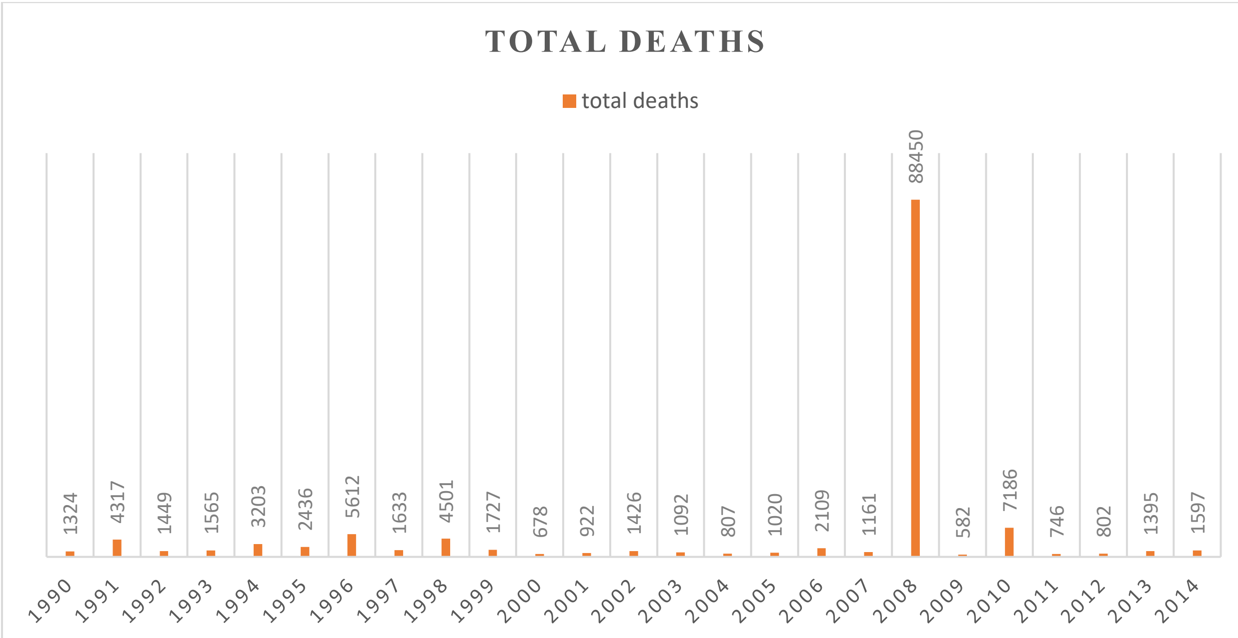
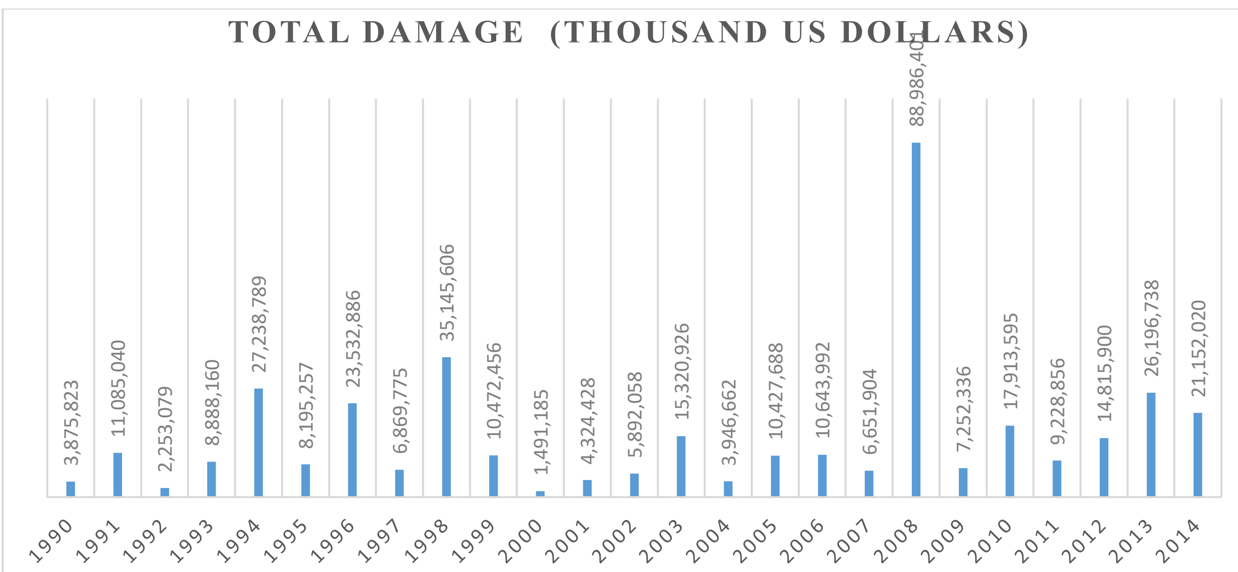


Figure A2. Annual Total Economic Damage from Natural disasters in China



Data source: The EM-DAT.

APPENDIX B: Robustness Check (Based on the EM-DAT Data)

In the main paper, we use the physical intensity measures of disasters to model their impact on fiscal behaviors. While the intensity measures (constructed using objective geophysical and meteorological information) capture the exogeneity of natural hazards, they may not well reflect the actual social disturbance and scope of damage caused by a disaster. In this section, we draw on the EM-DAT disaster losses data to create an alternative measure of disaster severity as a robustness check. Specifically, we create a variable measuring the number of significant disasters in a province-year. We define a large event if it has resulted in at least 100 deaths or $1 million economic damage (at constant 2000 price). This procedure has reduced our original sample from a total of 618 recorded disasters to 105 large-scale events (17%).

We note that for the disaster events that have affected more than one provinces, EM-DAT only reports the total losses (e.g., fatalities and economic damage). We reconstruct the province-level disaster loss by using the population of affected provinces in a single event (assuming that more densely-populated areas suffer more disaster damage) as the weight and then calculate the sum of disaster damage (from all events) for each province-year observation. It should be noted that our weighting scheme may not accurately capture the distribution of damage across all affected provinces and may bring noise to our estimation. We perform additional tests by comparing our EM-DAT weighted data with the province-specific disaster losses data drawn from the Chinese Environmental Statistical Yearbook (available for the 2003-2014 period only) and find that disaster damage statistics from the two data sources are highly correlated.

We estimate the fiscal impact of large disaster incidents using the same panel VAR model as described in the main paper (equation 1). Figure A3 displays the estimated DMFs of the dynamic disaster impacts on each fiscal variable (i.e., total tax revenues, total government spending, and total intergovernmental revenues) in year *t* (when a disaster shock occurs) through year *t* +10. The pattern of fiscal responses, as shown in the figure, is largely consistent with what we have found in the main paper (using the aggregate disaster intensity index): total provincial government spending and intergovernmental revenues from the central government both increase immediately when a natural disaster strikes and later decline over time, while disasters seem to have little effect on the total tax revenues collected by a provincial government.

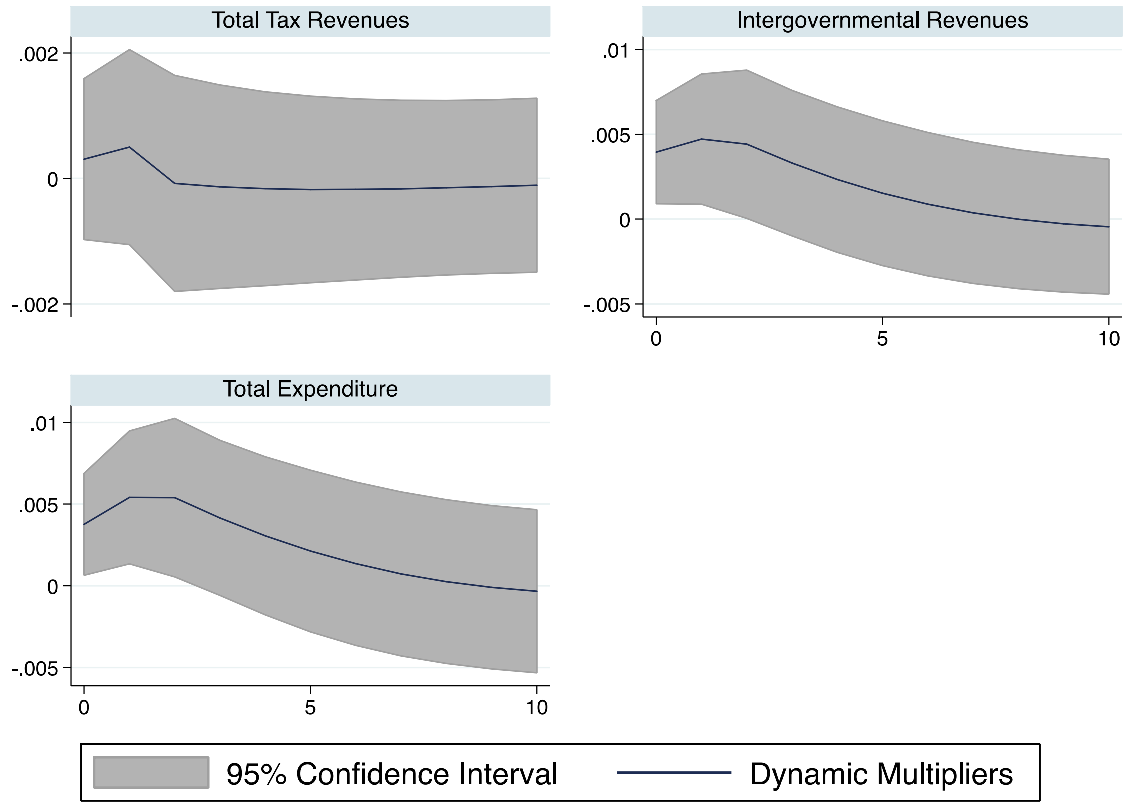
Table A2 summarizes the DMF point estimates in each year from year *t* through year t+5, as well as the cumulative fiscal impact of natural disasters over this period. In Panel A, we find that both total spending and intergovernmental transfers increase by almost 0.4 percentage points of GDP immediately when a large disaster event occurs. The disaster impacts on the two fiscal outcomes peak in the next year (*t+1*) and gradually decline thereafter, although such an effect still remains statistically significant in year *t+2*. Cumulatively, one large-scale disaster increases provincial government spending and intergovernmental revenues by 2.4 and 2 percentage points of GDP, respectively, in the following five years. The disaster impact on total tax revenues is statistically insignificant in all individual years and cumulatively. Overall, we show that using large-scale disaster counts based on the EM-DAT data produces similar results and therefore suggests the robustness of our main findings.

Table A2. Dynamic Fiscal Impact of Large-scale Disaster Incidents

	year t	year t+1	year t+2	year t+ 3	year t+ 4	year t+5	Cumulative
Tax Revenues	0.0003	0.0005	-0.0001	-0.0001	-0.0002	-0.0002	0.0003
	(0.0006)	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0019)
Total Expenditure	0.0038**	0.0054***	0.0054**	0.0042*	0.0031	0.0021	0.0239***
	(0.0016)	(0.0020)	(0.0024)	(0.0024)	(0.0024)	(0.0025)	(0.0055)
Intergovernmental Revenues	0.0040***	0.0047**	0.0044**	0.0033	0.0023	0.0015	0.0202***
	(0.0015)	(0.0019)	(0.0022)	(0.0021)	(0.0021)	(0.0021)	(0.0050)

Notes: For Monte Carlo simulations, 500 replications were used in the computation of standard errors as indicated in parentheses. *** $p < 0.01$, ** $p<0.05$, * $p<0.1$

Figure A3. Dynamic Fiscal Impact of Natural Disasters (large event counts)



APPENDIX C: Robustness Check of Baseline Findings

As discussed in the paper, we note that the panel VAR estimation we employed in this study does not correct for degrees of freedom from differencing out year fixed effects. As such, the standard errors we present may be understated. As a robustness check, we use bootstrapped standard errors (demeaning the year fixed effects within each redraw) instead of performing the Monte Carlo-based simulation in our panel VAR routine. In Table A4, We show that the estimates of standard errors using both approaches are highly similar.

Table A4. Dynamic Fiscal Impact of One Unit Change in the Disaster Intensity Index

Panel A. DMF Point estimates with standard errors generated from Monte Carlo simulations

Variables	year t	year t+1	year t+2	year t+ 3	year t+ 4	year t+5	cumulative
Total expenditure	0.2497**	0.4095**	0.5475***	0.5648***	0.5372***	0.4797***	2.7884***
	(0.1142)	(0.1616)	(0.1818)	(0.1809)	(0.1792)	(0.1753)	(0.4096)
Intergovernmental Revenues	0.2907**	0.4961***	0.6494***	0.6261***	0.5690***	0.4914***	3.1228***
	(0.1227)	(0.1638)	(0.1856)	(0.1856)	(0.1809)	(0.1733)	(0.4166)
Total tax revenues	0.01459	0.0112	-0.01119	-0.0243	-0.0347	-0.0423	-0.0867
	(0.0453)	(0.0596)	(0.0626)	(0.0600)	(0.0559)	(0.0528)	(0.1393)

Notes: For Monte Carlo simulations, 500 replications were used in the computation of standard errors as indicated in parentheses.
*** $p < 0.01$, ** $p<0.05$, * $p<0.1$

Panel B. DMF Point estimates with bootstrapped standard errors

Variables	year t	year t+1	year t+2	year t+ 3	year t+ 4	year t+5	cumulative
Total expenditure	0.2497***	0.4095***	0.5475***	0.5648**	0.5372**	0.4797**	2.7884***
	(0.0870)	(0.1579)	(0.2290)	(0.2489)	(0.2478)	(0.2313)	(0.5117)
Intergovernmental Revenues	0.2907***	0.4961***	0.6494***	0.6261***	0.5690**	0.4914**	3.1228***
	(0.0986)	(0.1763)	(0.2356)	(0.2389)	(0.2261)	(0.2031)	(0.4958)
Total tax revenues	0.01459	0.0112	-0.01119	-0.0243	-0.0347	-0.0423	-0.0867
	(0.0287)	(0.0451)	(0.04921)	(0.0441)	(0.0394)	(0.0358)	(0.1004)

Notes: We estimated the panel VAR model by differencing out year fixed effects and then estimate the bootstrapped standard errors (with 1000 replications), which are reported in parentheses.
*** $p < 0.01$, ** $p<0.05$, * $p<0.1$