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SUPPLEMENTARY INFORMATION

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Global spread of local cyclone damages through urban trade networks

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Supplementary Information

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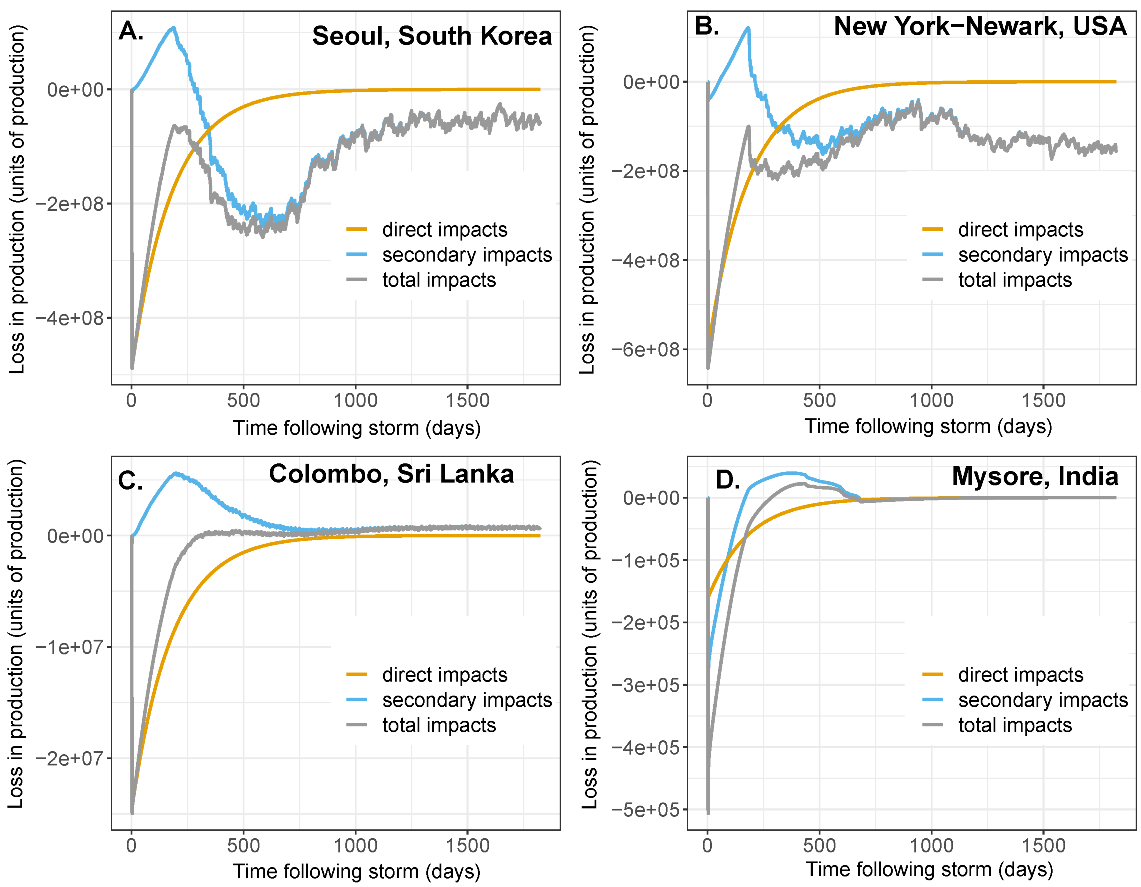
Supplementary Discussion

Additional Model Information

We explore the development of direct and secondary impacts for five years following a single large cyclone in each of four cities (Supplementary Figure 1). The four cities exemplify diverse network characteristics in terms of number of strong supply relationships and dependence on the network for industrial inputs: New York City, United States (high number of strong supply relationships, high dependence on the network for industrial inputs); Seoul, South Korea (high number of strong supply relationships, low dependence on the network for industrial inputs); Mysore, India (low number of strong supply relationships, high dependence on the network for industrial inputs); and Colombo, Sri Lanka (low number of strong supply relationships, low dependence on the network for industrial inputs). In each scenario, we simulate a large cyclone damaging 15% of industrial infrastructure in each city, which is similar to the magnitude of damage created by the largest storms in the historical cyclone dataset.

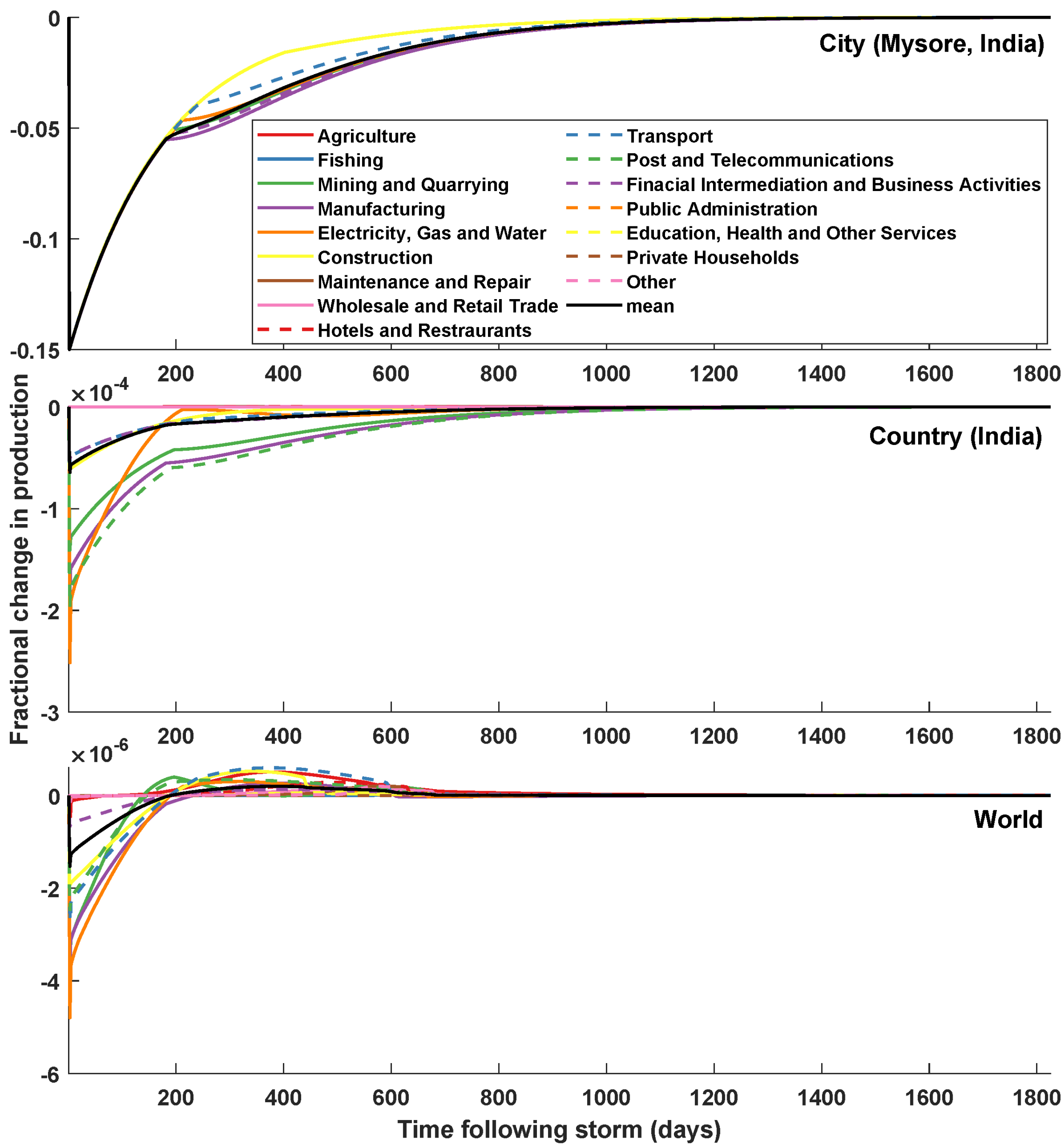


Supplementary Figure 1. Direct, secondary, and total impacts versus time following a single large storm striking Seoul, New York City, Colombo, and Mysore.

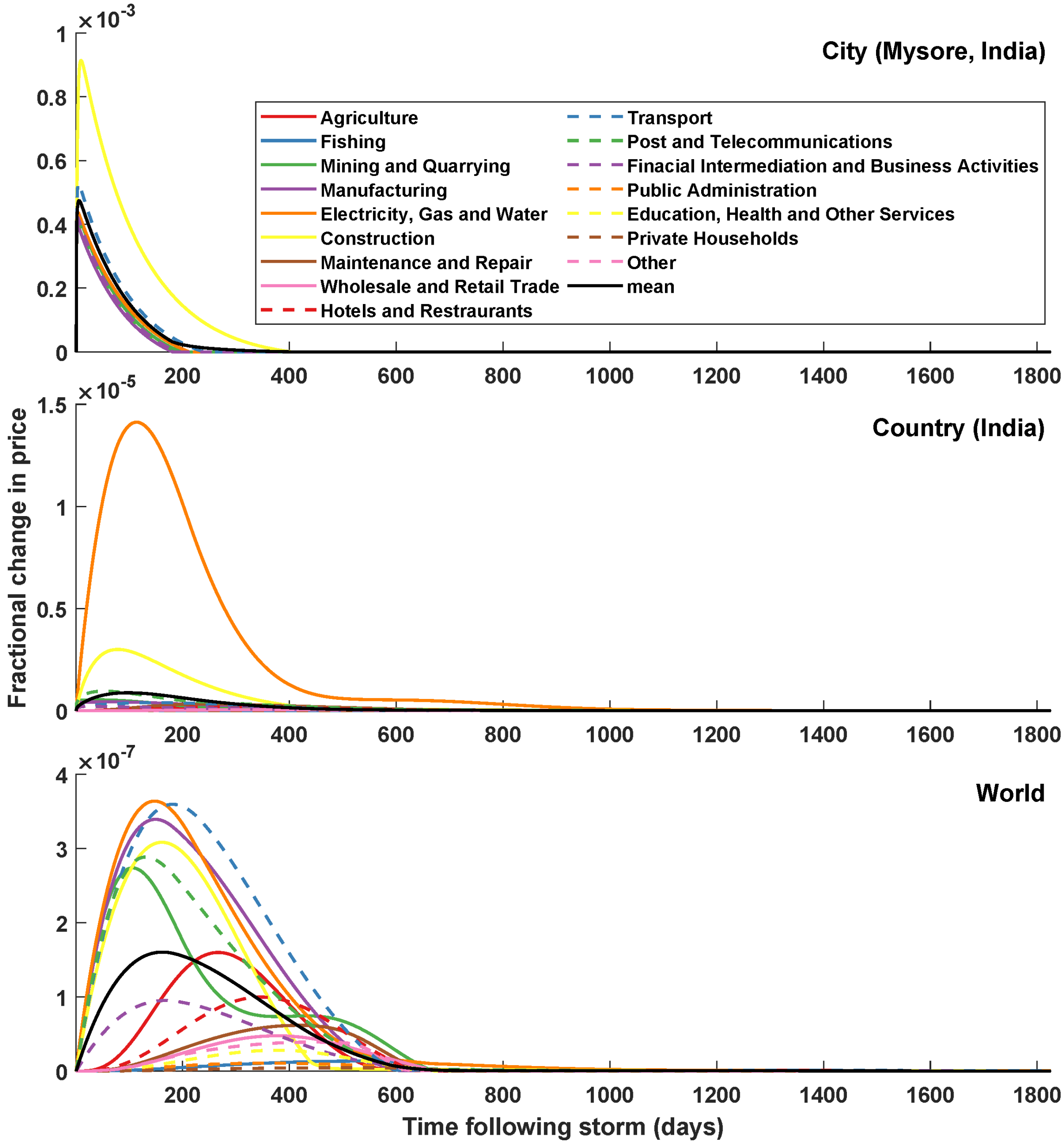
Impacts unfold in four distinct phases, with variation among the test cases depending on the particular size and network characteristics of each city:

1) In the days immediately after a storm, adverse secondary impacts are observed in all four cases, resulting from price spikes that reduce productivity throughout the network (Supplementary Figure 3).
2) In the months after the cyclone, beneficial secondary impacts emerge (Supplementary Figure 2). Demand for industrial inputs in the construction sector increases to accommodate increased demand for construction outputs for reconstruction of damaged productive capital, increasing production overall in other parts of the world to satisfy increased demand to construction.
3) A second wave of adverse secondary impacts emerges between months 10 - 30 for storms in the largest cities, Seoul and New York City. Over this time period, material shortages resulting from the initial shocks limit production for some supplier cities, nonlinearly reducing production throughout the network. These are not observed for impacts in small cities, for which material shortfalls can be more readily compensated by alternate suppliers. This pattern has been noted in other investigations of supply chain systems, for example, by Inoue & Todo (1) in their investigation of supply chain dynamics in Japan. Todo and Inoue (2) found that industrial substitution may dampen this nonlinear cycling, however, our model does not include industrial substitution.
4) Production rates stabilize and secondary impacts decay. For impacts to small cities, production returns to baseline levels throughout the network with no observed long-term adjustment to network behavior. Impacts to large cities can result in long-term shifts in production toward new suppliers. Alternate suppliers are engaged to compensate for shortfalls in material supplies as the industrial network recovers. Overproduction in these cities may persist in the long-term following recovery.

Our model represents the industrial economy as 16 sectors. Price and industrial production dynamically adjust in a manner that varies by city. Changes in production by sector and price are shown for the cyclone strike on Mysore, India in Supplementary Figures 2-3, with impacts displayed for Mysore, for India, and for cities globally.



Supplementary Figure 2. Fractional change in production versus time at the city, country, and global scale by industrial sector for a single large storm striking Mysore, India.



Supplementary Figure 3. Fractional change in unitary industrial input price versus time at the city, country, and global scale by industrial sector for a single large storm striking Mysore, India.

Model Comparisons

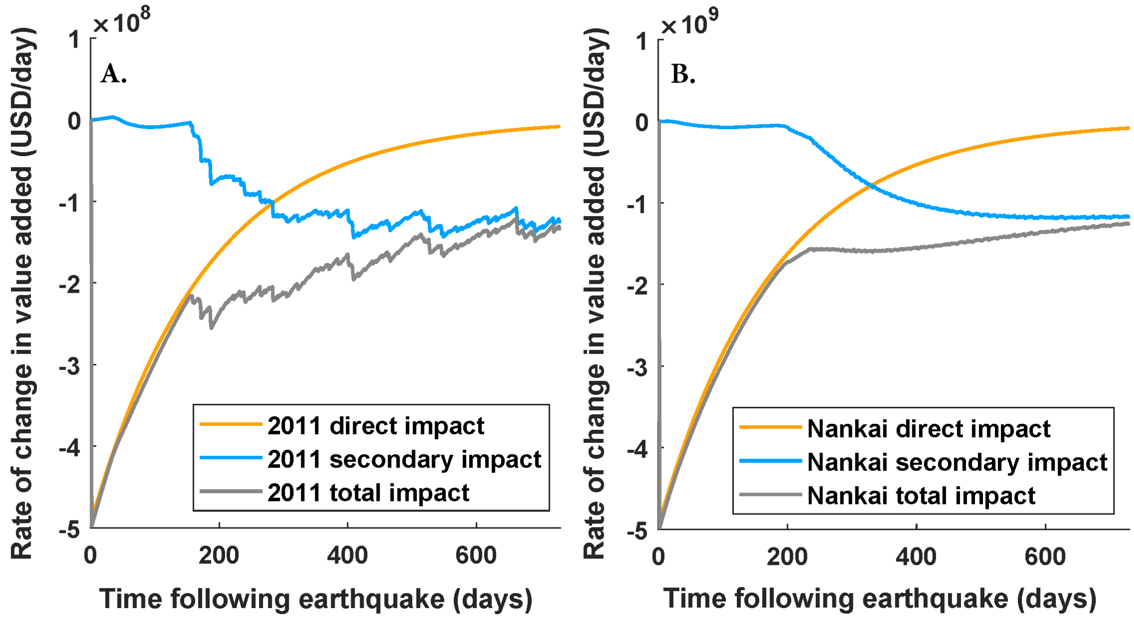
We developed three additional model scenarios to compare the model against previously studied examples of secondary impacts resulting from hazards.

Earthquake in Japan

Direct and secondary impacts to the economy of Japan have been calculated for major earthquake damage in 2011 and for a hypothetical catastrophic Nankai earthquake (1). We developed versions of our model to simulate the direct and secondary impacts resulting from damages similar to those modeled by Inoue & Todo (1). Direct and secondary impacts are considered only for Japan in this version of the simulation to compare behavior with results from Inoue & Todo (1). Damages from the 2011 earthquake and the hypothetical Nankai earthquake are estimated as 220 BUSD and 2,195 BUSD, respectively (1). We simulate earthquake damages to three cities significantly affected by the disaster: Tokyo, Osaka, and Nagoya (1). Fractional loss of productive capital in each city resulting from an earthquake is calculated as the ratio of earthquake damages to total fixed capital stocks in the three cities (4, 5). From this we estimate fractional damages to productive capital in the three affected cities of 4.0% and 40% for the 2011 earthquake and the Nankai earthquake, respectively.

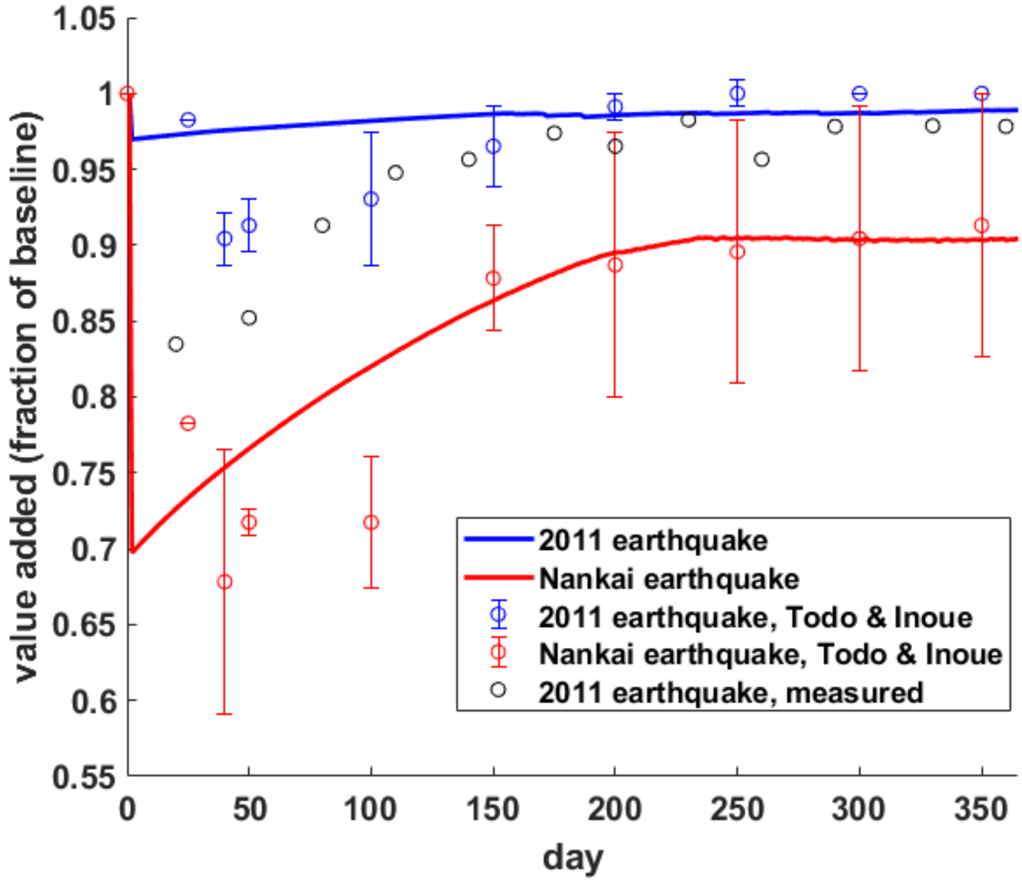
	2011 Earthquake (Todo & Inoue)	2011 Earthquake, (This article)	Nankai Earthquake (Todo & Inoue)	Nankai Earthquake, (This article)
Total Impacts*	1.49e11 (2.73)	9.61e10 (1.60)	7.05e11 (12.9)	8.62e11 (14.4)
Secondary Impacts*	1.48e11 (2.71)	1.95e10 (0.33)	6.75e11 (12.4)	9.63e10 (1.60)
Direct Impacts*	1.30e9 (0.02)	7.65e10 (1.28)	2.99e10 (0.55)	7.66e11 (12.8)

Supplementary Table 2. Adverse direct, secondary, and total impacts to value added in USD, with % change in baseline value added shown in parentheses, for the economy of Japan calculated using the model described in this article and reported by Inoue and Todo (1).



Supplementary Figure 4. Direct (orange), secondary (blue), and total impacts (grey) to the Japanese economy in value added USD versus time for 2011 earthquake (A) and Nankai earthquake scenarios (B).

We simulate direct, secondary, and total impacts resulting from these two scenarios, reported as value added to facilitate comparison for five years following the earthquakes (Supplementary Figure 4). Baseline value added in our simulation is slightly larger than that reported by Inoue & Todo for 2011 because we simulate the industrial economy in 2012 (Supplementary Table 2). For both scenarios, our simulation produces similar total impacts over the first year to those estimated by Inoue & Todo, differing by factors of 1.7 and 1.1 for the 2011 earthquake and Nankai earthquake scenarios, respectively. Estimates of fractional total impacts follow similar trajectories over time (Supplementary Figure 5), but differ significantly in magnitude and timing.



Supplementary Figure 5. Fractional total impacts on economy of Japan versus time for 2011 earthquake (blue), and Nankai earthquake (red) scenarios, and measured fractional loss following 2011 earthquake (black). Findings from (1) reproduced as circles with $\pm 1\ s.d.$ error bars.

Our model allocates a greater share of total impacts to direct impacts than secondary impacts, whereas the Inoue & Todo model finds the reverse outcome. As a result, greatest daily adverse impacts in our model occur immediately owing to direct impacts, whereas the greatest daily adverse impacts in the Todo and Inoue model are primarily secondary impacts and are relatively delayed until ~day 40.

The timing of secondary impacts varies between the two models, with adverse secondary impacts peaking after 12 months in our model compared with approximately 3 months in the Inoue & Todo model. This may be, in part, due to differences in the representation of freight transit. Our model represents delays in supply shortages as a function of freight travel time, whereas the Inoue & Todo model does not represent time lags. Shipping time delays in our model serve both as additional buffered inventory (shipments en route before a hazard augment supply inventories) as well as a delay to material shortages.

Differences in model behavior between the two studies may also be related to accounting of direct impacts. In both studies— Inoue & Todo and ours—direct damages are calculated as the product of fractional damaged productive capital (fraction of factories and infrastructure destroyed by a hazard) and baseline production in the absence of an impact. Total direct impacts are the sum of these daily production deficits over time. Secondary impacts are production deviations throughout the network excluding direct impacts.

Differences in the relationship between damages and ratio of malfunctioning productive capital may explain relatively low total impacts in our 2011 earthquake scenario relative to the Inoue & Todo model. In our main model, damaged productive capital is a linear function of cyclone wind speed. In our model comparison scenarios, ratio of malfunctioning productive capital is the ratio of total earthquake damages to fixed capital stock. Direct impacts scale approximately linearly with ratio of malfunctioning capital in our model—recovery of productive capital occurs at a fixed rate. In contrast, the Inoue & Todo model generates a nonlinear relationship between damages and direct impacts. The Nankai earthquake is expected to generate damages greater than the 2011 earthquake by a factor of 10. In our simulation, direct impacts also scale by a factor of 10 between the two scenarios, however, Inoue & Todo direct impacts scale by a factor of 23 (Supplementary Table 2). This suggests differences in the dynamics of direct impacts between the models or initialization of damaged productive capital.

Rate of recovery to damages may also contribute to differences in direct impact magnitude. Rate of recovery is inversely proportional to direct impacts—rapid reconstruction, for example, allows production to return to baseline more quickly and reduces the total quantity of production lost to direct impacts. In our model, recovery occurs over 6 months, whereas the Inoue & Todo model represents faster recovery of about 40 days. This difference in parameterization provides partial explanation for the difference in the magnitude of direct impacts.

Hurricane Harvey

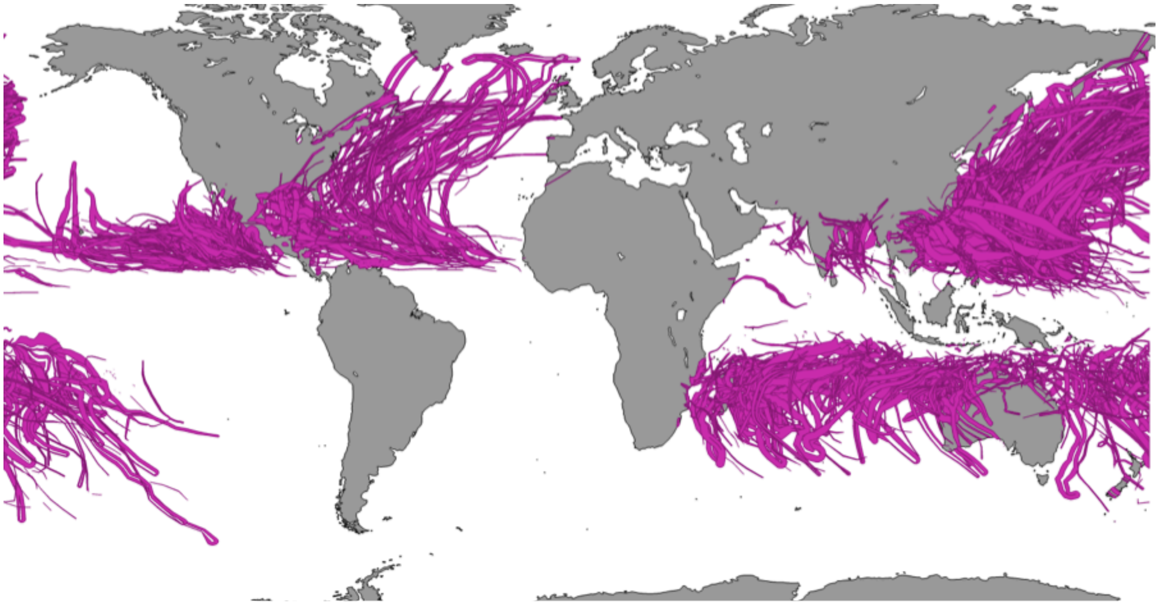
According to the US Federal Reserve, Hurricane Harvey (August, 2017 in the Gulf of Mexico, with landfall near Houston, TX) resulted in 0.9% loss of US economic activity over the first month, with 1/4 losses from secondary impacts and 3/4 of losses from direct impacts (6). Our simulation of Hurricane Harvey produces 0.46% loss of production in the US, with 1/5 adverse effects from secondary impacts and 4/5 owing to direct impacts. We found that our simulation produces fractionally smaller impacts on the US economy than were observed historically over the month following the storm. Differences between our model and the US Federal Reserve's estimate might be explainable as follows:

i) Hurricane Harvey resulted in significant flooding in Houston. Our model uses wind speed as an indicator for damages, and as a result, would have underestimated the impacts of this particular hurricane.

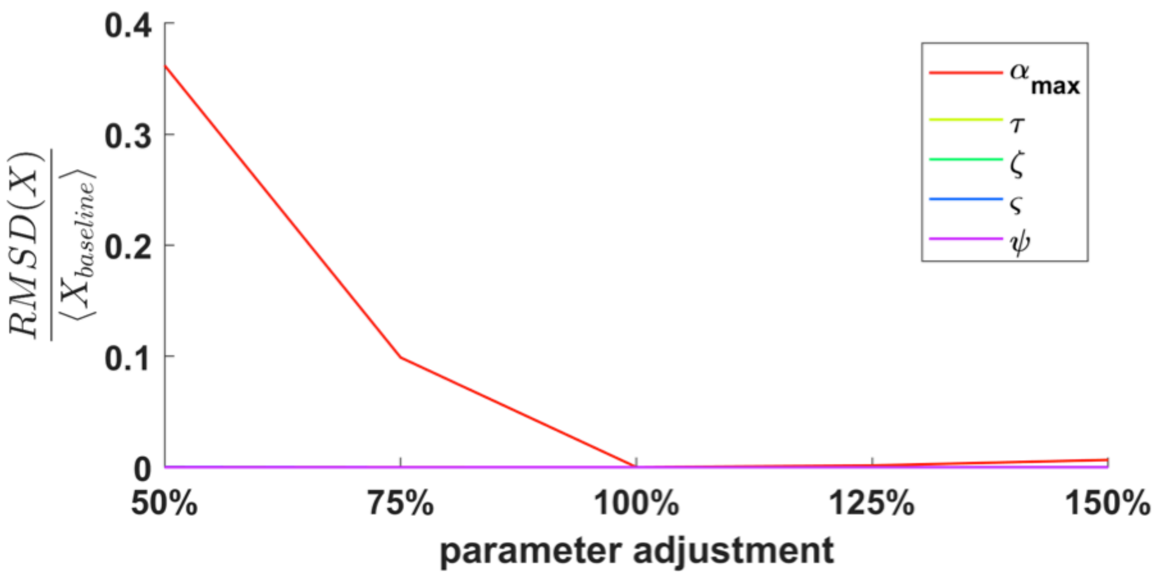
ii) Our simulation focuses on damages within cities. For this run, we simulated impacts only to Houston and Corpus Christi for lack of more detailed storm impact data. The actual storm additionally affected smaller cities and economic activity outside of cities altogether (for example, fossil fuel extraction in the Gulf of Mexico).

iii) We focus on the long-term recovery dynamics of cities to damages, but neglect some of the immediate effects resulting from business decisions during and immediately after a storm. For example, our model does not consider the closure of businesses in the immediate aftermath of a major storm such as this.

Supplementary Figures



Supplementary Figure 6. Cyclone tracks (purple polygons) between 1968 and 2009 (3).



Supplementary Figure 7. Root-mean square deviation of supply output normalized by baseline parameter output. Parameters are varied between 50% and 150% of the baseline value, with 100% representing the baseline parameter. Parameter sensitivity is calculated among 40 randomly selected storms from the dataset.

Supplementary Tables

		Affected by Secondary Impacts														
		South-Central Asia	Southern Europe	Northern Africa	West/Middle/ Southern	South America	West Asia	Oceania	Western Europe	Eastern Europe	East Africa	South-East Asia	North America	East Asia	Central America	Northern Europe
Secondary Impact Source	South-Central Asia	-4.6 E+04	9.6 E+03	1.6 E+03	2.3 E+03	6.9 E+03	5.7 E+03	3.8 E+03	9.6 E+03	8.9 E+03	3.2 E+02	1.6 E+03	3.3 E+04	2.2 E+04	1.6 E+03	8.5 E+03
	Southern Europe	5.1 E+02	-4.3 E+03	2.4 E+02	2.9 E+02	1.1 E+03	8.1 E+02	5.4 E+02	1.7 E+03	1.1 E+03	3.9 E+01	4.1 E+02	4.0 E+03	3.0 E+03	2.0 E+02	1.4 E+03
	Northern Africa	5.7 E+01	1.5 E+02	-4.6 E+02	2.5 E+01	1.1 E+02	7.9 E+01	3.9 E+01	1.6 E+02	1.1 E+02	3.9 E+00	5.0 E+01	2.8 E+02	2.3 E+02	1.9 E+01	9.7 E+01
	West/Middle/ Southern Africa	3.3 E+01	7.9 E+01	1.4 E+01	2.6 E+01	5.9 E+01	5.1 E+01	3.4 E+01	8.9 E+01	5.8 E+01	3.9 E+00	4.0 E+01	2.6 E+02	1.9 E+02	1.2 E+01	6.5 E+01
	South America	1.6 E+03	7.6 E+03	7.5 E+02	7.0 E+02	-2.1 E+04	3.0 E+03	-1.3 E+02	-4.9 E+03	6.0 E+03	-2.8 E+02	1.4 E+03	-8.0 E+03	-1.3 E+04	-2.7 E+03	5.4 E+03
	West Asia	1.5 E+02	3.2 E+02	5.1 E+01	7.3 E+01	2.5 E+02	2.0 E+02	1.5 E+02	3.7 E+02	2.2 E+02	1.2 E+01	1.2 E+02	1.1 E+03	7.8 E+02	4.9 E+01	2.6 E+02
	Oceania	6.6 E+03	1.4 E+04	1.7 E+03	2.2 E+03	9.4 E+03	5.4 E+03	-2.5 E+04	1.3 E+04	1.0 E+04	3.5 E+02	3.9 E+03	3.3 E+04	2.4 E+04	2.1 E+03	9.6 E+03
	Western Europe	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00	0.0 E+00
	Eastern Europe	2.1 E+02	3.6 E+02	6.4 E+01	7.5 E+01	2.3 E+02	1.8 E+02	-8.0 E+01	2.5 E+02	5.7 E+02	9.6 E+00	8.9 E+01	7.7 E+02	2.6 E+02	7.2 E+01	3.3 E+02
	East Africa	1.1 E+03	1.9 E+03	3.6 E+02	9.1 E+02	1.5 E+03	1.3 E+03	8.0 E+02	2.0 E+03	1.9 E+03	-7.2 E+03	8.2 E+02	5.9 E+03	4.3 E+03	3.0 E+02	1.7 E+03
	South-East Asia	3.0 E+04	5.9 E+04	9.1 E+03	1.5 E+04	5.0 E+04	3.4 E+04	2.1 E+04	5.8 E+04	4.7 E+04	1.6 E+03	-3.0 E+04	2.1 E+05	1.4 E+05	1.1 E+04	4.9 E+04
	North America	1.1 E+05	4.2 E+05	5.4 E+04	6.2 E+04	-1.8 E+05	1.4 E+05	-2.1 E+03	-3.5 E+05	3.5 E+05	-1.4 E+04	3.0 E+04	-1.2 E+06	-1.1 E+06	5.4 E+04	3.3 E+05
	East Asia	3.4 E+05	1.5 E+06	2.1 E+05	2.8 E+05	-7.9 E+05	2.0 E+05	-4.4 E+05	-1.6 E+06	1.4 E+06	-5.9 E+04	-8.1 E+03	-2.0 E+06	-3.8 E+06	2.6 E+05	9.0 E+05
	Central America	3.4 E+03	9.2 E+03	1.3 E+03	1.7 E+03	8.1 E+02	4.4 E+03	1.7 E+03	2.4 E+03	8.0 E+03	6.0 E+01	2.3 E+03	1.1 E+04	5.6 E+03	2.5 E+03	7.7 E+03
	Northern Europe	4.6 E+03	-6.9 E+03	2.6 E+03	1.1 E+03	-1.3 E+04	-7.7 E+02	-6.6 E+03	-1.5 E+04	1.1 E+04	-1.0 E+01	-3.2 E+03	-2.5 E+04	-9.6 E+03	2.5 E+03	-1.6 E+04

Supplementary Table 1. Total secondary impacts ('000 units of production) originating with storms striking cities in 14 global regions (vertical column) and affecting cities in 14 global regions (horizontal column) for 1209 historical storm simulations. Beneficial secondary impacts (increased production) are represented by positive values and adverse secondary impacts (suppressed production) are represented by negative values. A Unit is the quantity of production outputs exchanged in USD. Data are aggregated, thresholded and displayed in Figure 1.

Supplementary References

1. Inoue, Hiroyasu, and Yasuyuki Todo. "Firm-level propagation of shocks through supply-chain networks." *Nature Sustainability* 2.9 (2019): 841-847.

2. Todo, Yasuyuki, Kentaro Nakajima, and Petr Matous. "How do supply chain networks affect the resilience of firms to natural disasters? Evidence from the Great East Japan Earthquake." *Journal of Regional Science* 55.2 (2015): 209-229.

3. U.N.E.P/GRID-Geneva. (2011). *Tropical cyclones wind speed buffers 1969-2009*. http://sids.grid.unep.ch/layers/geonode:GRID_Cyclones_buffers.

4. International Monetary Fund. "IMF Investment and Capital Stock Dataset, 2017". (2017). https://www.imf.org/external/np/fad/publicinvestment/data/data122216.xlsx

5. International Monetary Fund. Estimating Public, Private, and PPP Capital Stocks. (2017).

6. US Federal Reserve System. "Natural Disasters and the Measurement of Industrial Production: Hurricane Harvey, a Case Study". (2018). https://www.federalreserve.gov/econres/notes/feds-notes/natural-disasters-and-the-measurement-of-industrial-production-hurricane-harvey-a-case-study-20171011.htm