**ONLINE APPENDIX A: ECONOMIC THEORY AND NATURAL HAZARDS**

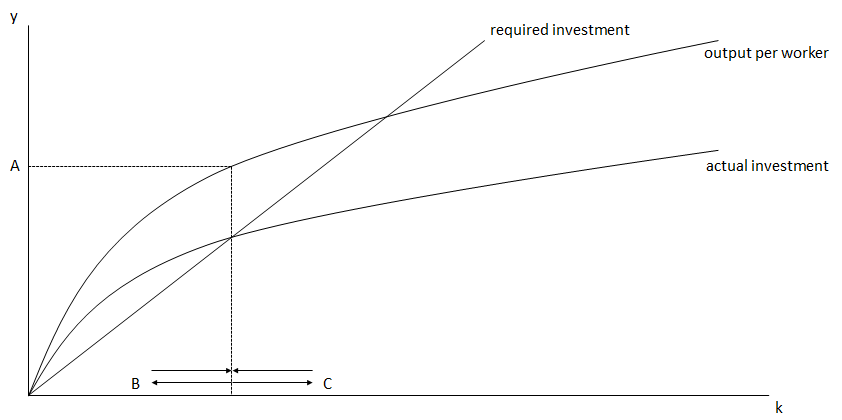
This appendix first describes the main macroeconomic families that can be used to theorize about the economic impacts of natural disasters, which are summarized in Table 1 in the main manuscript. Table A1 provides more detail by adding the most relevant model assumptions, giving a brief description of the model family, and listing key references. Next, regional economic models are reviewed, which are summarized in Tables A2–3.

**A1. Macroeconomic Models and Natural Hazards**

The starting point for our review of the relevant theoretical framework for the analysis of natural hazards is the neoclassical Ramsey-Solow-Swan growth model. This model has been applied to the study of economic impacts of natural hazards by several authors (Albala-Bertrand 1993; Lusardi 1998; Skidmore 2001; Skidmore and Toya 2002; Keen et al. 2003; Noy and Nualsri 2007; Loayza et al. 2009; Okuyama 2003) and can be summarized in the following key equations:

where *Y* is output, *A* is an index of labor augmenting productivity, *K* is the capital stock, *L* is labor, and *α* is the output elasticity of capital. Subscripts label discrete time, and capital depreciates over time at rate *δ* and accumulates through investment *I*, which, in equilibrium, is equal to savings, given by a fixed share, *s* of income *Y.[[1]](#footnote-1)* The steady-state equilibrium in this model is found by expressing all variables in per effective worker terms and setting capital per effective worker constant at:

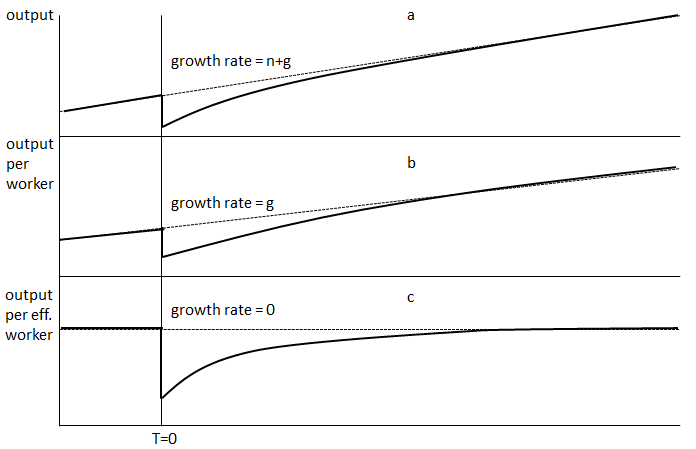
where an asterisk denotes the steady state, *g* is the exogenous and constant growth rate of productivity*, n* is the growth rate of the population, and *k* is defined as *K/AL*. A natural disaster will shock the economy out of steady-state equilibrium, and the model predicts how it will return to its stable steady state. The impact of a natural disaster is best illustrated in the well-known Figure A1 below.



*Figure A1. Analysis of natural hazards in the neoclassical Ramsey-Solow-Swan growth model*

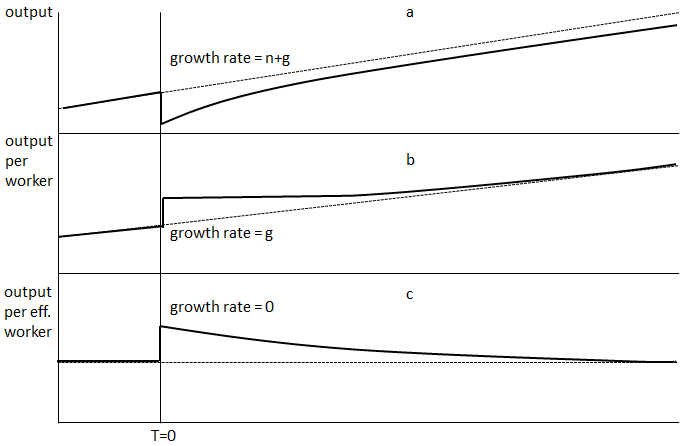
In this figure, on the vertical axis is per worker output, *y*, and on the horizontal axis is per worker capital, *k*. The line labeled “output per worker” traces output per worker as a concave function of capital per worker, as in equation 1. The line labeled “actual investment” represents a fixed share *s* of that level of output. The line labeled “required investment” traces the level of investment per worker needed to maintain a given level of capital per worker. Where the two latter lines intersect is the steady-state level of capital per worker. Point A then represents the corresponding steady-state level of output per worker. A well-known result in the Solow model is that, in the absence of exogenous technical change, there is no per capita growth in the long run. In the long term, the linearly increasing depreciation will inevitably catch up with the concave savings and investment that a higher level of capital per worker can sustain. The impact of a natural disaster can now affect the equilibrium through different channels.

First, the natural disaster (e.g., a storm or earthquake) can destroy part of the capital stock. In that case, the economy will experience a reduction in capital per worker and move away from the steady state to the left (point B). From there, given that savings rate, population growth, productivity growth, and depreciation rate do not respond to the shock, the economy will then save more per effective worker than is needed to maintain the diminished capital stock. The economy will, therefore, gradually return to the steady state, and the predicted patterns in output, output per worker, and output per effective worker are given in panels a–c of Figure A2 below.



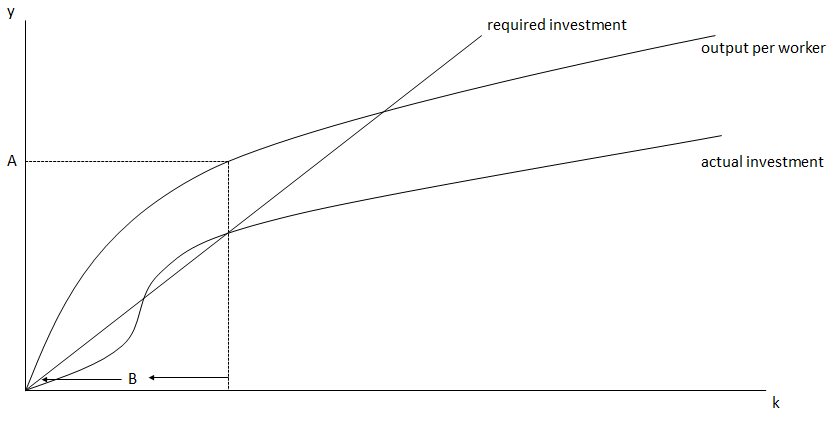
*Figure A2.* *Predicted pattern in output (a), output per worker (b), and output per effective worker (c) when the economy returns to the steady state after a disaster* *destroys part of the capital stock*

Secondly, a disaster that diminishes the (working) population while leaving the capital stock intact (e.g., a flood or disease) can have the mirror-image effect. It moves the economy to point C in Figure A1 and reverts to the steady state because total savings fall short of what is needed to maintain the capital stock. In panels a–c of Figure A3, however, it can be seen that total output now falls to a permanently lower level as output per worker and per effective worker jumps up and falls back to the original steady state.



*Figure A3.* *Predicted pattern in output (a), output per worker (b), and output per effective worker (c) when the economy returns to the steady state after a disaster diminishes the (working) population*

This simple model already provides researchers with a basic prediction of the impact of natural hazards on the economy. It predicts a short-run negative shock on total output, and depending on the relative direct impacts on population and capital, the impact on per (effective) worker output is positive or negative but will always revert to the pre-disaster levels over time. To the best of our knowledge, only some papers have yet investigated the impact of hazards on the other parameters in the basic Ramsey-Solow-Swan model. That is, natural disasters and hazards may affect (precautionary) saving behavior (Skidmore 2001; Berlemann et al. 2015), the average expected economic lifetime of assets (Loayza et al. 2012), and the productivity of labor or all factors of production and/or the exogenous rates of productivity and population growth. One could analyze the effects of such impacts by looking at changes in parameters *s*, *δ*, *α*, *A*, *g,* and *n*, respectively. Moreover, the model can handle more complex savings functions. A relevant extension here would be to introduce the so-called poverty trap by assuming savings are (close to) 0 when income is close to subsistence levels. The actual investment line in Figure A1 then becomes a nonlinear transformation of the production line and may intersect the required investment line multiple times, giving rise to multiple stable and unstable steady-state equilibria. Figure A4 illustrates how a disaster can then cause an economy to pass a critical threshold and fall back into the poverty trap.[[2]](#footnote-2)



*Figure A4. Analysis of natural hazards in the neoclassical Ramsey-Solow-Swan growth model while accounting for the poverty trap*

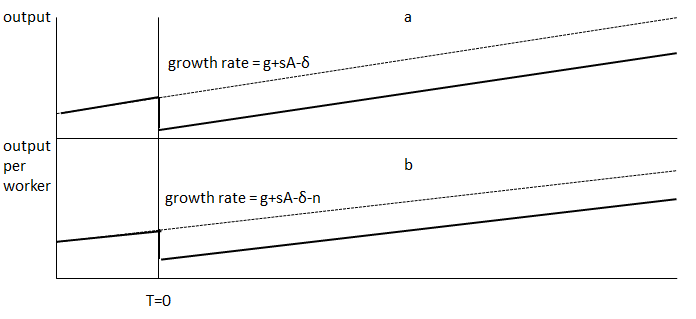
Another important extension would be lifting the closed economy assumption. We return to this issue below, but in an open economy, investment is no longer necessarily equal to savings. In the extreme case of perfect capital mobility in a small open economy, the return to the steady state is instant because the marginal productivity of capital cannot deviate from the global interest rate. Of course, reconstruction takes time in reality, and instant recovery is an extreme prediction, but one could derive the hypothesis that well-integrated regions with access to finance and resources from other parts of the country (and world) should recover faster from natural disasters. The available evidence (Noy 2009) indeed seems to support this, although, it is hard to empirically disentangle this effect and establish causality.

More important for our discussion is the development in macroeconomic thinking about growth that built on the Ramsey-Solow-Swan foundations. This development focused on endogenizing growth as it is clear from the model above that in steady state, growth in per capita output can only come from productivity growth, and, in the end, the object of study (growth) is therefore assumed rather than explained in neoclassical growth models. Solow’s (1957) own empirical work on US states showed that over 90 percent of cross-state variation in output per worker must be attributed to exogenous productivity differences, and this “measure of ignorance” attracted much scholarly attention.

A special case of the Ramsey-Solow-Swan model that features endogenous growth in a rudimentary form emerges when we assume capital is facing constant returns (*α*=1). In these so-called *AK* models (Barro and Sala-I-Martin 1995; McGratten 1998), the production function is replaced by:

*Y=AK*

and output per worker will continue to expand as long as capital grows at a positive rate. This is the case when *s+g>n+δ*. Now the savings behavior of consumers will affect not only the level but also the growth rate of income per capita. As a corollary, a crucial insight of these models is that shocks to the capital stock now have permanent negative effects on the level and growth rate of the economy. The predicted response to a negative shock on population is now simply a permanent increase in income per capita because labor is not assumed to directly affect output. More interestingly, the impact of a negative shock to the capital stock shifts the economy permanently onto a lower growth path for both total and per capita output, as shown in panels a and b of Figure A5.



*Figure A5. Analysis of natural hazards in the AK growth model*

The issue of technical change becomes more interesting for our purpose if we return to an older class of models. This somewhat forgotten class of models assumes that all new knowledge developed following the process described above actually diffuses into the economy in the form of (capital) goods and products. These vintage models of technical change and diffusion assume that the capital goods produced in a given year (vintage) embody the technological knowhow of that year and, once produced and put into operation, will not change their technical specifications. Although this model is arguably less applicable to capital goods of a less material nature (e.g., software that can be updated), it still fits the reality of many capital goods today. Few have the knowledge embodied in a modern car, yet many have the skills to operate one. They, thus, benefit from knowledge they do not possess but is embodied in the capital good they operate. Destroying the car does not destroy the knowledge, but replacing the destroyed car with a new one will automatically update the knowledge that is embodied in it. At the level of a region hit by a natural disaster, the destruction of the capital stock can thereby be followed by a rapid updating of knowledge embodied in the region’s capital stock. Keeping track of capital vintages is obviously very data intensive but fits rather well the data collected and used in input-output tables. As the latter are typically put together at the country level, and vintage models seem to be out of fashion, there are no empirical papers we are aware of that test this hypothesis directly—that is, the hypothesis that a natural disaster wipes out old and new vintage capital alike, and reconstruction then rapidly replaces that with the latest vintage capital, causing productivity to rise. Instead, authors have proposed and tested this intuition with the “build back better” hypothesis (Skidmore and Toya 2002) that attributes all post-disaster total productivity gains to the updating of embodied knowledge in rebuilt capital without explicitly linking this to the evolution of the vintage structure of the capital stock. The evidence for this hypothesis is mixed and scarce. A more careful theoretical development of that hypothesis using vintage models may well prove relevant in bringing this literature forward.

After knowledge accumulation was identified as the prime driver of long-run economic growth, researchers (i.e., Acemoglu 2008) turned their attention to its root causes. Fundamentals like geography, institutions, and even luck were considered, and a consensus seems to now appear that institutions are at the root of economic growth and disparities in per capita incomes today (Acemoglu et al. 2002). Like the stock of knowledge, however, such institutions have no spatial dimension. Institutions, broadly defined by North (1991) as “the manmade rules of the game,” exist in societies that share and perpetuate them, and, of course, societies occupy space. However, the existence and functioning of the institutions are explicitly assumed not to depend on the space they exist in because growth theory is interested in the institutions that promote growth independent of geography. Natural hazards and disasters, in contrast, are always and anywhere a local phenomenon. Models that seek to identify the fundamental mechanisms of economic growth are, therefore, not very suitable for developing testable hypotheses on the (short-run) economic effects of natural hazards beyond the rather obvious hypothesis that, all else being equal, good institutions help cushion the impact of natural hazards and speed up recovery. In contrast, we do believe natural disasters are very suitable to study some of the most pertinent questions in growth theory.

The key problem in modern empirical growth literature is the identification of causal mechanisms. Institutional quality is obviously correlated positively with income levels and growth. Given the difficulties in accurately measuring a multidimensional and fuzzy concept like “institutional quality,” however, makes this positive correlation almost a tautology in empirical tests. Given the way we measure institutional quality and economic growth, it is hard to imagine the correlation could be anything else than positive.[[3]](#footnote-3) To handle this econometric identification problem, Acemoglu et al. (2001) present a complicated two-stage instrumental variable approach in which they use fifteenth-century settler mortality rates to instrument for institutional quality and identify the positive causal effect (of private property rights protection). It is beyond the scope of this paper to review the entirety of empirical literature on institutions and growth (see, for an overview, Acemoglu 2008). We only propose here that the hypothesized positive contribution of institutions on growth can also be identified when a clearly exogenous shock like a natural disaster event can be shown to differently affect regions under different institutional regimes. If institutions have a differential effect on economic growth across societies, they are likely to also have a differential effect on the recovery process following a negative shock that does not affect the evolution of the knowledge stock. For example, Raschky (2008) shows that common indicators of institutional quality at the national level indeed correlate with the efficiency at which countries handle natural hazards. The link to economic growth and the moderation of indirect and long-run economic effects, however, has not been made in this paper.

*Table A1. Mainstream macroeconomic model families, their key assumptions, model features, references, and references in context of natural disasters*

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| --- | --- | --- | --- | --- |
| **Model family** | **Key assumptions** | **Key model features** | **Key references** | **Key references on natural disasters** |
| Input-Output Models | Constant returns to scale | In input-output models, fixed proportions technology implies a loss in capital results in proportional losses in output that are distributed over the value chain. | Ten Raa (2006) | Hallegatte (2008), Hallegatte (2014), MacKenzie et al. (2012). See also appendix B. |
| Zero elasticity of substitution |
| Exogenous technical change |
| Diminishing returns to inputs |
| Computable General Equilibrium Models | Constant returns to scale | In computable general equilibrium models, agents can substitute for resources that are destroyed. Prices will adjust to incentivize such substitution throughout the value chain. The difference between short- and long-run impacts depends on the assumed price stickiness. | Dixon and Jorgenson (2013) | Carrera et al. (2015). See also appendix C. |
| Positive elasticity of substitution |
| Exogenous technical change |
| Diminishing returns to inputs |
| Vintage Capital Models | Constant returns to scale | In vintage capital models, any accelerated depreciation of capital implies an increase in productivity growth. The build-back-better hypothesis is assumed in these models. | Whitaker (1966), Benhabin and Rustichini (1991) | Hallegatte and Dumas (2009), Barone and Mocetti (2014), Cuaresma et al. (2008), Kim (2011), Noy and Vu (2010) |
| Constant elasticity of substitution |
| Exogenous technical change |
| Diminishing returns to inputs |
| Neoclassical Growth Models | Constant returns to scale | The neoclassical growth model predicts a return to steady state. The position of that steady state can change only if parameters change. | Ramsey (1928), Solow (1957), Cass (1965), Koopmans (1965), Acemoglu (2008) | Albala-Bertrand (1993), Okuyama (2003), Berlemann et al. (2015), Skidmore and Toya (2002), Skidmore (2001), Lusardi (1998), Keen et al. (2003), Loayza et al. (2012), Noy and Nualsri (2007) |
| Unit elasticity of substitution |
| Exogenous technical change |
| Diminishing returns to inputs |
|  |
| AK Models | Constant returns to scale | AK models link output and output per worker to the level of capital in use. This implies that negative shocks to the capital stock have lasting negative impacts on output per worker. | Barro and Sala-I-Martin (1995), Acemoglu (2008) |  |
| Single input factor |
| Semi-endogenous technical change |
| Constant returns to input(s) |
|  |
| Learning Models | Increasing returns to scale | In learning models, the level of productivity depends on variables like cumulative production or investment. Destruction of capital or labor could stimulate learning and productivity growth in reconstruction. | Wright (1936), Yelle (1979), Arrow (1962), Juninger et al. (2010) | Cuaresma (2010) |
| Constant elasticity of substitution |
| Semi-endogenous technical change |
| Diminishing returns to inputs |
|  |
| Endogenous Growth Models | Increasing returns to scale | Endogenous growth models rely on knowledge creation and commercialization as the sources of output and output per worker growth. These processes are not directly affected by natural hazards. | Aghion and Howitt (1992, 1998), Romer (1986, 1990), Jones (2005), Grossmann and Helpman (1991b), Acemoglu (2008) | Cuaresma (2010) |
| Constant elasticity of substitution |
| Endogenous technical change |
| Diminishing returns to inputs |
|  |
| Institutional Growth Theory | Increasing returns to scale | Institutional growth models point to the importance of sound institutions as the fundamental causes of economic growth and development. To the extent that such institutions are affected by natural hazards, there can be long-run effects. More likely is that the same institutions that explain growth also explain hazard recovery. | Nelson (2002), Acemoglu (2008) |  |
| Constant elasticity of substitution |
| Endogenous technical change |
| Diminishing returns to inputs |
|  |
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**A2. Regional Economics and Natural Hazards**

Our discussion of the macroeconomic approaches to growth so far has shown that the assumption on the role of space and geography makes these models difficult to apply directly to the economic analysis of natural hazards. The (often implicit) assumption in macroeconomic models is that space is “uniform abstract” (Capello 2015). From the Solow model to the more recent institutional growth models and from the more micro-oriented vintage capital models to the pure macroeconomic knowledge-driven endogenous growth models, space is assumed uniform in the sense that all space under the aggregation level considered is assumed to be identical. Even if researchers use regional or local-level data, the capital, labor, and technology are measured at, and assumed to be, evenly distributed within the area under study. Space is, therefore, abstract in the sense that distance and geography are simply assumed not to matter. That assumption is particularly troubling in the context of a localized shock, like a natural hazard. We, therefore, now turn to the discussion of models in regional economics. Its subdisciplines of location economics and urban economics offer models that address questions like: Why do economic activities locate where they do? What explains the size distribution of cities? More closely related to and inspired by macroeconomic models discussed above are subdisciplines of regional growth and local development that ask questions like: why do some places develop differently than others?

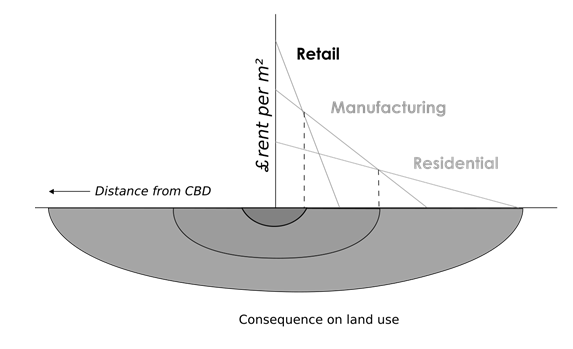
The earliest models of location can be traced back to the work of, e.g., Weber (1909), Hotelling (1929), and Hoover (1948), presenting models of industrial location choice. These early models explain the spatial distribution of economic activity as the result of a rational decision to locate in a specific place. Assuming constant transportation costs per unit of distance, these models start by drawing concentric circles of iso-transport costs. The optimal location choice then minimizes these costs for a given geographical distribution of input and output markets and, assuming free entry of firms, the concentric circles will overlap and result in firms locating in space and supplying their goods to hexagonal market areas as illustrated in Figure A6 below.

Different assumptions on the economies of scale and production costs can then be invoked to explain patterns of spatial distribution in a location equilibrium. These simple early models can explain both dispersion and agglomeration of economic activity. The early models abstracted from geography and assumed a perfectly uniform space as well as production at a point serving demand that is uniformly distributed in space. To explain the existence and spatial structure of urban centers, however, this assumption was reversed, and researchers like von Thünen (1826), Alonso (1960), and Muth (1961) proposed models that assume production in space, serving demand concentrated in a point (urban center). In these models, it is land rent that is the price that equilibrates the location market, and these models explain why high-value-added activities with high transportation costs tend to locate closer to the centers of demand than those with low value added and low transportation costs. The von Thünen model (1826) was developed to explain the allocation of farmland around (medieval) urban centers and is nicely captured in the land rent equation:



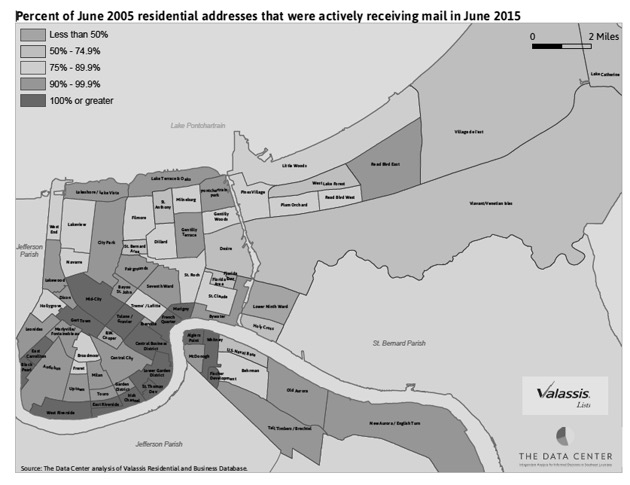
where *r* is the land rent, *d* is the distance from the urban center, *p* is the price of the good, *c* is the unit cost, *τ* is the transportation cost, and *x* is the quantity produced (and transported to the urban center). In this very basic model, it is already clear that land prices respond to distance from the nearest urban center in a linear way. This prediction is perhaps less relevant for the analysis of natural hazards, but the parameters identified in the equation above can also be linked to the impacts of natural hazards to derive hypotheses on how land prices should respond. If a natural disaster makes a region less accessible, this can be interpreted as an increase in transportation costs for given distance. The destruction of capital and/or labor availability can be modeled as a (temporary) rise in unit production costs, and limited local supply of goods can cause changes in final goods prices.

Alonso (1960) basically extended the von Thünen model by assuming price, *p*(*d*),and costs*, c*(*d*)—and, therefore, profits—depend negatively on distance from the city center to explain within-city spatial patterns. Again, land rent is the price that equilibrates supply and demand for location at every point in space, and in a model with a very similar mathematical structure, Alonso (1960) explains household location choices. These models all result in a so-called “rent curve” that traces equilibrium land rent as a function of distance from the urban center, as in Figure A6 below.



*Figure A6. The Alonso (1960) rent curve that traces equilibrium land rent as a function of distance from the urban center (CBD)*

Combining the von Thünen and Alonso models by assuming at the city limits the land rent equals the land price of the surrounding agricultural region, we obtain an equilibrium allocation of activities in concentric rings around the assumed city center. We now must abandon the assumption of uniform space common in these models to link them to natural hazards and natural disasters. However, it is rather straightforward to derive predictions on land rent in a specific location (e.g., a flood plain) as a function of the ambient natural hazard risk to derive the hypotheses that the literature has tested quite extensively in the hedonic pricing studies mentioned above. If natural hazards and disasters affect the (expected) unit costs and final goods prices at specific locations differentially, this has clearly predictable effects on the willingness of rational economic agents to pay for locating in these areas. The impact on land rent of disruptions to and destruction of infrastructures affecting transportation costs from and to given locations is perhaps less straightforward and appears much less researched in the empirical literature. From the equation above, however, we can derive the hypothesis that also land rent in unaffected areas will respond if a disaster changes the transportation costs to and from that area. It is then an empirical matter if the adjustment to a new location equilibrium involves a return to the old situation (when transportation costs return to their old levels faster than economic agents respond to gradually changing relative land rent), or the disaster can have a lasting effect on the location equilibrium that prevails (firms and people relocate faster, and transport costs shift permanently). An example of the former is Hurricane Sandy that hit New York City but did not cause any permanent shifts in location and land rent patterns. An example of the latter is Hurricane Katrina. As the map in Figure A7 shows, there are whole areas of New Orleans that remain abandoned, and land rents adjusted permanently even decades after.

*Figure A7. The low percentage of residential areas in New Orleans that is actively receiving mail indicates abandoned areas after Hurricane Katarina*

The field of urban economics then turned to models to explain the empirically very apparent hierarchy in urban systems that these early models cannot explain. The pioneering work of Christaller (1933) and Lösch (1940) introduced an elegant framework, known as central place theory, for explaining the emergence of urban systems with a core and periphery and explaining the spatial distribution of economic activity over these different places. The Christaller model was formalized by Beckman and McPherson (1970). In its simplest form, the model predicts that the size distribution of cities of different hierarchical order is:

where there are *n* order cities, *s* is the number of order *n-*1 satellites an *n* order urban center serves, *c* is the population living in the city relative to the population it serves, and *r* is the population of rural settlements that perform no urban functions. The intuition behind this equation is that, knowing the population in rural settlements, we can derive the population of urban centers of any order. That population obviously increases with the order of the city, *n*. It is also positive in *s* as more satellites implies the same share of a larger population served lives in the higher-order city. For the same reason, given the number of satellites, the population is positive in the share of a population that needs to concentrate in a city to provide the higher-order service for the entire population, *c*. In its original formulation, these parameters were assumed constant throughout the urban system hierarchy. Despite these rather restrictive assumptions, however, the model preformed remarkably well in predicting the number and sizes of urban centers in larger urban systems in Germany.

Lösch (1940) then relaxed the assumption of constancy and strict proportionality, and by using Chamberlin’s model of imperfect competition, he showed that proportionality would emerge endogenously in general spatial equilibrium. Again, later scholars proposed formalization, and the model could explain the size distribution of cities, the distances between them, and their roles in the urban system they belong to.[[4]](#footnote-4) Their relevance for the analysis of natural hazards flows from the fact that natural hazards and disasters have the potential to disrupt not only the regions and locations they hit directly. Through the here-modeled interdependencies among urban centers of different hierarchical order, it is possible to hypothesize that the urban system to which the affected region belongs will also see temporary or even permanent adjustments. Taken at face value, the early central place models would predict a full recovery. These models assume homogenous demand in space, constant transportation costs, and a full decoupling of supply and demand in space. That is, there are no mechanisms to differentially affect a specific part of the urban system. Space is still assumed to be homogenous, and there are no dynamic feedback loops that can cause convergence to other equilibria than the single stable one derived above.

To effectively study the impact of natural hazards and disasters that often strike only parts of urban systems, we must turn to models that assume diversified space—that is, models that allow for differences in resource availability, supply and demand, and innovative capacity across space. Among the first to conceptualize such models was Perroux (1955), who proposed, “Development does not appear everywhere at the same time; it becomes manifest at points or poles of development, with variable intensity; it spreads through different channels, with various effects on the whole of the economy” (Perroux 1955, 308, translation by Capello 2015). The implications of this statement for the analysis of natural hazards are profound because once we consider that economic growth and development are localized in space, the effects of natural disasters on the overall economy become location specific. A hurricane with given strength and intensity will have a profoundly different effect on the economy of a region or nation depending on where exactly it hits.

Perroux (1955) proposed a simple model in which substantial emphasis is put on the existence of a dominant firm in an area. That firm would then affect the development in the region through classical Keynesian income multiplier effects, Leontieff’s technological multiplier effects up the production column in an input-output framework, and investment accelerator effects, again concentrated in the upstream sectors connected to the dominant firm. The introduction of transportation costs then explains why more and more firms locate in the area, creating a growth pole, where the additional activity has all the above effects and creates a concentration of demand for unrelated goods and services as well. In development economics, this logic was applied to study the role of multinational firms and FDI. Many public policy and development initiatives to attract dominant, multinational firms to jumpstart growth in backward regions and countries have opened our eyes to the fact that the presence of a large, dominant firm is not a sufficient condition for a growth pole to emerge. There may, in fact, be backlashes when these dominant firms drive out local firms by increasing wage and production costs while competing for local demand. Moreover, large, multinational firms can easily channel the benefits abroad while imposing large externalities on the local community, going unchallenged as they capture local politicians and regulators and lock a region into a low growth equilibrium to keep opposition weak. These experiences have led to the insight that the emergence of a growth pole depends on the simultaneous and complementary development of many things.

Innovation scholars (e.g., Hägerstrand 1952 and, later, Grilliches 1957 and Mansfield (1961) studying and modeling the adoption of innovations as a source of local development quickly arrived at similar conclusions. The first models assumed rather mechanical logistic models, where adoption of innovation was assumed to be a function of random contact and parameterized by an assumed saturation level and diffusion speed, much like the spread of an infectious disease. However, scholars quickly realized that the ability and willingness to adopt innovations differed markedly between places. Grilliches (1957) and Mansfield (1961) hypothesized that economic distance would be more important than geographical distance and introduced local differences in profitability to explain the variations in parameters across regions. The study of innovation dynamics, however, also quickly revealed that places differ not only in their physical location but also in the relationships and networks that operate within and across them. Scholars found that the availability of high-quality public infrastructures, specialized human capital, innovative capabilities, entrepreneurial spirit, and cultural attitudes matter a great deal for the economic success of regions (Acs et al. 1994; Audretsch and Feldman 1996). The theorizing about such complex interacting features at the local level, however, has inevitably become less formal and precise.

Capello (2015) mentions and describes the development of industrial district theory and theories developed to explain optimal city sizes as the result of balancing benefits and costs of agglomeration, but as the models were extended and enriched to account for empirical facts at odds with previous work, they lost their tractability. For example, to explain the higher growth rates of smaller cities, regional economists proposed the theory of “borrowed size,” proposing that small cities could borrow the benefits of size from other nearby cities in the same urban system. Others then asserted that proximity to a large center could also limit small cities in their growth as they can no longer develop into higher-order cities themselves. This implies that anything goes in many of these models, making them much less useful for our purpose here. What we can take away from these insights, however, is that also in the analysis of natural disaster impacts, it pays to consider the network in which affected locations operate. Effects of disasters, both positive and negative, are transmitted across space and upset the initial location equilibrium, the spatial allocation of resources, and the urban hierarchy. By using natural events as strictly exogenous shocks to urban systems, perhaps here, as in the empirics of economic growth, the empirical analysis of natural hazards can bring important insights to the questions that regional economists are engaging in.

The diversified-relational conceptualization of space led not only to largely intractable predictions on the static locational equilibrium. As the 1980s saw the development of endogenous, innovation growth theory in macroeconomics, regional economists turned their attention to the ability of local economies to generate and absorb knowledge and innovation. Again, they quickly realized a diversified-relational conceptualization of space was essential in doing so in the sense that locations can be characterized by their ability to adopt, imitate, and improve on innovations, and such abilities depend crucially on the relations among agents in the location. Scholars explored the importance of different concepts of proximity for the spillovers of knowledge that generate the increasing returns in knowledge-driven growth models. That is, the beneficial external effects of knowledge creation follow from the fact that others can use that knowledge to create new ideas, products, and services that in turn create economic growth. Building on the work of Grilliches and Mansfield, scholars explored concepts ranging from simple geographical proximity to economic, relational, institutional, and cognitive proximity. Knowledge creation and the closely related high-tech innovative economic activity tend to be geographically concentrated (Camagni and Capello 2013; Capello and Lenzi 2013) in urban centers of relatively high orders and/or very clear specializations. Research has shown own R&D efforts are more productive in the presence of other firms’ R&D located nearby (e.g., Audretsch and Feldman 1996), and diversified local innovative capacity is important for local firms and sectors. As it is hard to imagine, however, in times of rapid diffusion of ICT technology, that physical distance should be an important barrier to information and knowledge exchange, scholars started digging deeper and revealed that it is the relationships among actors that create a milieu for innovation and knowledge exchange (Capello 1999a, 1999b, 2001). Keeping pace with developments in macroeconomics, the regional economic literature then also turned to the institutional framework conditions that support (or hinder) the collective learning process that characterizes the milieu, and Howells (1999) and others regionalized the theory of national innovation systems proposed by Lundvall (1992) to describe the intricate complexities of interacting institutions, attitudes, and incentives that drive innovation at the regional level. Evolutionary economists (Nelson 1993), more inclined to model decision making as bounded rational and conceptualizing dynamics as resulting from the emergence of diversity and selection on fitness, then proposed that innovation at the regional level also requires cognitive proximity in the sense that innovators are more likely to build on what they know, creating strong path dependencies and the development of related variety.

Once more, the richness of these models and concepts in describing the wide variety of development experiences in the data has a downside in the fact that the theory is so rich that it can explain almost any observed pattern in the data. Regions may grow, stagnate, or decline under the same set of observed characteristics, and measurement of such complex, multidimensional concepts as relational proximity or the quality of the regional innovation system risks constructing tautological measures (the quality is high when the region grows) that are unsuitable for rigorous hypothesis testing. Also, the direction of predicted effects is often far from clear. Still, from this literature we can also take away that regions affected by natural events are to be considered part of a system that will not only propagate the shock itself and return to or converge on a new static equilibrium but may also affect the dynamic interactions that drive the regions’ long-run economic development. Exploring the impact of natural hazards on specialization patterns across space may well enlighten the theorizing on regional development.

A final group of models to be discussed in this section conceptualizes space as diversified-stylized. In that group, the problem of “anything goes” is addressed, while these models retain the property of having diversified space, allowing for differential impacts of similar shocks on different locations. This development was pioneered by Krugman (1979), who, by combining increasing returns to scale and imperfect competition, founded a “new economic geography.” In an elegant model featuring an agricultural sector producing at constant returns under perfect competition and a manufacturing sector producing with increasing returns under monopolistic competition and introducing transportation costs, Krugman (1979) showed that growth in a region will depend crucially on the net effect of two opposing forces. On the one hand, entry of a manufacturing firm into a region causes a competition effect, driving down profitability in the region due to induced price and market share reductions, whereas, on the other hand, it causes an offsetting market size effect as more labor migrates to the region with higher wages. Alternatively, Venables (1996) proposed replacing the migration-driven market size effect by a cost reduction effect that emerges from upstream intermediate demand increases to better fit the European context of low labor mobility, and in a more dynamic approach, one could also conceptualize the positive externality emerging from knowledge spillovers as in the endogenous growth models. The new economic geography models developed based on this work all share the property of diversified-stylized space such that the local specifics of actual regions are stylized, and the models generalize across space. Their nonlinearity, however, typically implies they have multiple equilibria and can generate very complex dynamics in response to shocks. The introduction of natural hazards and disasters in the context of these models, therefore, shows promise. The models have sufficient richness to accommodate different responses but at the same time certainly do not allow for “anything goes.” Empirical research using the exogenous shocks that natural events represent can trigger different responses in the local economy affected, but these different responses are conditional on parameters and assumptions that are much more precise and testable than in the descriptive models discussed above.

The analytical rigor of the diversified-stylized space models comes at the cost of ignoring the relational aspects of local development. Capello (2015) claims the way forward for regional economics is, therefore, to focus on local absolute comparative advantage in a dynamic sense—that is, on the ability to construct and maintain an absolute competitive advantage that ensures the region a place in the global division of labor. She presents the MASST model (Capello 2007) as an example of what such models would look like. They combine the strengths of uniform-abstract space macroeconomic growth models with the strengths of diversified-relational regional development models to analyze the propagation of top-down and bottom-up shocks and dynamics at the local level. The study of the economics of natural hazards will benefit greatly from such efforts as it is relatively straightforward to then introduce such shocks at the appropriate local level to derive both local, neighboring regions’ and aggregate national economic impacts in a coherent and consistent modeling framework.

*Table A2. Summary of regional economic model families*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model family** | **Key input variables** | **Key output variables** | **Predicted outcomes** | | | |
|  | **(initial shock)** |  | **Closed economy** | | **Open economy** | |
|  | | | **Short run** | **Long run** | **Short run** | **Long run** |
| Location Models | Capital (-) | {RGPi, RGP-i, RGPDensityi} | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Labor (-) | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,-,+} | {0,0,0} | {-,-,+} | {0,0,0} |
|  | Spillovers (-) | {-,-,+} | {-,+,-} | {-,-,+} | {-,+,-} |
| Land Rent Models | Capital (-) | {RGPi, RGP-i, LandRenti} | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Labor (-) | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,-,+} | {0,0,0} | {-,-,+} | {0,0,0} |
|  | Spillovers (-) | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
| Central Place Models a | Capital (-) | {RGPn, RGPn-1, PopDensityn} | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Labor (-) | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Spillovers (-) | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
| Growth Pole Models b | Capital (-) | {RGPgp, RGP-gp, Growthgp} | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
|  | Labor (-) | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
|  | Spillovers (-) | {-,-,-} | {-,-,-} | {-,-,-} | {-,-,-} |
| Innovation Diffusion Models c | Capital (-) | {RGPi, RGP-i, Growthi} | {-,+,0} | {+,+,+} | {-,+,0} | {+,+,+} |
|  | Labor (-) | {-,+,0} | {-,-,0} | {-,+,0} | {-,-,0} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,+,-} | {-,+,-} | {-,+,-} | {-,+,-} |
|  | Absorption Cost (+) | {0,0,-} | {0,0,-} | {0,0,-} | {0,0,-} |
| Spillover and Network Models | Capital (-) | {RGPi, RGP-i, Growthi} | {-,+,0} | {±,±,±} | {±,±,±} | {±,±,±} |
|  | Labor (-) | {-,+,0} | {±,±,±} | {±,±,±} | {±,±,±} |
|  | Recon Demand (+) | {+,+,0} | {±,±,±} | {±,±,±} | {±,±,±} |
|  | Transport Costs (+) | {-,+,-} | {±,±,±} | {±,±,±} | {±,±,±} |
|  | Absorption Cost (+) | {0,0,-} | {±,±,±} | {±,±,±} | {±,±,±} |
| New Economic Geography d | Capital (-) | {RGPn, RGPn-1, Growthn-1} | {-,+,0} | {0,-,0} | {0,0,0} | {0,0,0} |
|  | Labor (-) | {-,-,0} | {-,-,0} | {-,-,0} | {-,-,0} |
|  | Recon Demand (+) | {+,+,0} | {0,0,0} | {+,+,0} | {0,0,0} |
|  | Transport Costs (+) | {-,-,-} | {0,0,0} | {-,-,0} | {0,0,0} |
|  | Absorption Cost (+) | {0,0,-} | {0,0,-} | {0,0,0} | {0,0,0} |

*Note: Table contains family names (column 1), their key input variables, which are the point of entry for the disaster impacts (column 2), a vector of endogenous output variables, where RGP refers to regional gross product and subscript i refers to the region that these models typically cover, subscript n refers to the highest-order region and gp to the growth pole region (column 3), and short- and long-run predictions for a closed and open economy (columns 4 to 7). Labor is always assumed immobile. “Open” refers to trade in goods and services and capital. -, 0, +, and* ±, *respectively, stand for negative, zero, positive, and indeterminate effects on the listed output variables.* *a Assuming the central place (n) is directly affected. Impacts are not symmetric. b Assuming the growth pole region (gp) is directly affected. Impacts are not symmetric .c Assuming (new) technology is (largely) embedded in (new) capital equipment. d Assuming the advanced region (n) is hit. Impacts are not symmetric. Note: We list the prediction on growth for the lagging country (n–1). “Closed” refers to a two-country-region model.*

*Table A3. Regional economic model families relevant for natural disaster analysis, their key assumptions, model features, and references*

|  |  |  |  |
| --- | --- | --- | --- |
| **Model family** | **Key assumptions** | **Key model features** | **Key references** |
| Location Models | Uniform demand | Location models predict that economic activity is agglomerated or spread in space in location equilibrium. This location equilibrium can be upset temporarily or permanently by natural disaster shocks. | Weber (1909), Hotelling (1929), Hoover (1948), Salop (1979) |
|  | Production locates optimally |
|  | Constant transportation costs |
|  | Abstract uniform space |
|  | Agglomeration economies |
| Land Rent Models | Demand point | Land rent models assume demand is concentrated (in an urban center) and land rent adjusts to establish spatial equilibrium. Again, this equilibrium can be upset by natural disasters affecting land rents. | Von Thünen (1826), Alonso (1960), Müth (1961) |
|  | Production locates optimally |
|  | Constant transportation costs |
|  | Abstract uniform space |
|  | Agglomeration economies |
| Central Place Models | Heterogeneous demand | In central place models, the focus is on the structure of urban systems of *n*-order. It assumes a hierarchy of products and services. Natural hazards can upset the urban system depending on where they hit. | Christaller (1933), Lösch (1940) |
|  | Production locates optimally |
|  | Product-specific transport costs |
|  | Abstract uniform space |
|  | Agglomeration economies |
| Growth Pole Models | Uniform demand | In growth pole models, dominant firms constitute a growth pole (gp). The gp is the engine of growth for the region around it. If it is hit, the entire region around it suffers. | Perroux (1955) |
|  | Production locates optimally |
|  | Constant transport costs |
|  | Abstract diversified space |
|  | Agglomeration economies |
| Innovation Diffusion Models | Uniform demand | In these models, innovations diffuse as an infectious disease using logistic diffusion curves. The infection rate and vulnerable population can be determined by regional characteristics. Nongeographic concepts of distance and proximity were shown to matter. | Hägerstrand (1952), Grilliches (1957), Mansfield (1961) |
|  | Production locates optimally |
|  | Logistic diffusion |
|  | Diversified relational space |
|  | Heterogeneous absorptive capacity |
| Spillover and Network Models | Uniform demand | In these models, innovations diffuse through a variety of networks and relationships. This makes a region part of a network. The richness of the models implies predictions are not unequivocal, but disaster impacts ripple through the network. | Acs et al. (1994), Audretsch and Feldman (1996), Frenken et al. (2007) |
|  | Production locates optimally |
|  | Relationships as channels |
|  | Diversified relational space |
|  | Heterogeneous absorptive capacity |
| New Economic Geography | Symmetric demand | By introducing imperfect competition and increasing returns in stylized space, new economic geography models can explain the dynamic specialization pattern over space and time. They predict asymmetric effects of natural disasters; when more advanced regions are hit, effects will trickle down but not up. | Vernon (1966), Krugman (1979), Venables (1996), Grossman and Helpman (1991a) |
|  | Production locates optimally |
|  | Increasing returns to scale |
|  | Diversified stylized space |
|  | Imperfect competition |

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**ONLINE APPENDIX B: INPUT-OUTPUT MODEL STUDIES OF NATURAL DISASTERS**

Standard I-O models estimate how much production of goods by a specific sector consisting of a system of interacting industries is needed to meet a given level of demand, by accounting for all intermediate demands (and corresponding supplies). Production of each sector is used as input for other goods and services or to meet final consumer demand. I-O models aim to convert changes in industry production due to a shock to changes in final demand, which is then incorporated in the estimation of total economic losses caused by the shock, e.g., a natural disaster. This is done through an inverse or Leontief matrix of parameters, which estimates this total economic effect on the basis of a ratio of total gross output per unit of final demand. Another approach is taken by some supply-side I-O models that measure the impacts of constraint supply due to a shock by expressing production as a function of primary inputs, like labor, which can be (temporarily) limited in availability due to a shock. A restrictive assumption by such models is that supply generates demand. The inoperability I-O model (IIM) is a framework used by various natural disaster applications that captures the inoperability of a sector— defined as the relative degradation of its capacity to deliver its intended output— due to a temporary reduction in available labor or capital stocks after a disaster (Santos and Haimes 2004). This inoperability is often determined on the basis of assumptions, although recently some empirical work has been done to estimate such parameters (e.g., Kajitani and Tatano 2014). See Dietzenbacher and Miller (2015) and Oosterhaven (2017) for a more detailed discussion on the use and limitations of the IIM in modeling natural disaster impacts.

A number of studies applied the standard I-O framework or modifications of it to examine particular characteristics of economic impacts of disasters. For instance, Okuyama et al. (1999) used a two-regional I-O model to estimate economic impacts of the 1995 Kobe earthquake for the area directly impacted by the earthquake and the rest of Japan. Okuyama (2004) extended the I-O model with the so-called Miyazawa’s framework to link the location of production with the location of consumption to estimate the spatial impacts of the Great Hanshin Earthquake in Japan. Sohn et al. (2004) created a multiregional I-O model based on interregional commodity flows to estimate impacts of a hypothetical New Madrid earthquake in the United States. Although most I-O models operate on a rough geographical scale and assume homogenous disaster impacts in an area, Yamano et al. (2007) developed one with a refined geographical scale (five hundred square meters) using local data on economic activity to examine economic hotspots of damage caused by the 1995 Hanshin Awaji Great Earthquake in Japan. Moreover, several studies have developed I-O models of natural disaster impacts that to some degree overcome some of shortcomings of the standard I-O approach and/or examine particular mitigating factors of natural disaster impacts. The setup of these models and their main results are summarized in Table B1 and discussed below.

**B1. Price Changes, Supply Constraints, and Adaptation in I-O Models**

Hallegatte (2008) developed the adaptive regional input-output (ARIO) model to estimate the impacts on the economy of Louisiana due to Hurricane Katrina, which made landfall in New Orleans in 2005. The aim of the model is to assess the total economic cost of the hurricane, which consists of the indirect cost because of the disaster, defined as the reduction of the total value added by the economy, and the direct cost, which is the portion of the remaining value added that has to be used for reconstruction instead of regular consumption. The ARIO model is based on I-O tables of fifteen sectors that describe how each industry uses inputs from other industries to produce commodities. A distinction is made between inputs that are produced locally and can be affected directly by the disaster and those that are imported. A local I-O table links production in each industry with demand from other industries, local final demand, exports, and reconstruction.

Standard I-O models usually assess disaster shocks on the demand side, called backward linked losses, and neglect supply-side impacts. The ARIO model accounts for constraints in production originating from damaged production capacity of a specific industry, unavailability of production inputs due to damaged production capacity of other industries, and unavailability of imported commodities due to disruption of transportation. In case of production bottlenecks, a rationing scheme is assumed, which entails proportional reductions in demands in which intermediate consumptions by other industries are given priority, and less priority is given to exports, final local demand, and reconstruction. The disaster enters the model framework through the destruction of capital of companies (which lowers their production capacity by an equal proportion) and households, which are assumed to be repaired and be fully covered by insurance. This implies that reconstructions do not reduce demand for other goods and result in new demand. Impacts of the disaster on labor supply are not considered, which can be viewed as a limitation of the model. A certain degree of adaptation of supply occurs when, in the case of a production shortage, companies can gradually increase supply by using overproduction capacity, which can be interpreted as adding production and equipment to production processes for reconstruction. While prices are often kept constant in standard I-O applications, the ARIO model aims to accommodate price increases that occur due to the demand surge in the reconstruction phase after a disaster, while production capacity is (at least temporarily) reduced. Price increases are modeled as a linear function of underproduction in an industry. A restrictive assumption is that prices and related profits do not influence production. Local final demand and export demand depend on both prices and a quantity of final demand based on pre-disaster prices. This final demand is influenced by a certain degree of adaptation to the disaster situation. In particular, the rationing of local demand in response to damaged production capacity is smaller when local customers can obtain commodities from outside the affected region. The rationing of export demand is smaller when the production in the affected region is highly specialized and external customers and businesses have less flexibility in demanding the goods elsewhere. The model assumes that the economy returns to pre-disaster production and consumption relationships. This implies that structural changes in the economy that may occur due to a disaster are not accounted for.

It should be noted that setting the parameters of the model is highly uncertain due to limited available data; especially for the behavioral equations that model adaptation and price responses, approximations on the basis of observations during other disasters or ad hoc assumptions of values had to be made (Hallegatte 2008). A sensitivity analysis shows that the overproduction parameters and adaptation characteristic times have the largest influence on results (Hallegatte 2008; Koks et al. 2015).

The ARIO model findings show that total value added reduces by 8 percent shortly after the shock by Hurricane Katrina, and then it increases due to reconstruction and overproduction. Reconstruction is completed after eight years, and total production is equal to the pre-disaster level after about six years. Total economic losses are estimated at $149 billion, of which indirect production losses are $42 billion. A comparison of sector production predicted by the ARIO model and data of actual production between 2004 and 2005 shows that the model prediction of a 2.8 percent decrease in production over the four last months of 2005 is an underestimation of the actual 4.5 percent decline. The models’ predicted declines in employment after the disaster, such as about 9 percent after two months, are close to the observed drops in employment. Moreover, the disaster is found to result in trade imbalances by reducing exports by up to 10 percent and reducing imports by 4 percent. Model simulations with varying levels of direct costs show that after direct losses reach $50 billion, the indirect losses increase nonlinearly with direct costs and can reach up to 100 percent of direct costs when the latter are as high as $200 billion.

Koks et al. (2015) adjust the ARIO model to estimate direct and indirect losses from flooding for a case study of the Rotterdam harbor area in the Netherlands. A catastrophe is used to estimate the direct losses to capital and labor per sector due to simulated flood events. A share of industry flooding is assumed to be related to a loss of labor per sector. While the standard ARIO model (Hallegatte 2008) only considers disaster impacts on production capital, the adjusted model by Koks et al. (2015) uses Cobb-Douglas functions to estimate the effects on production of both reduced capital and labor supply after a flood. These Cobb-Douglas functions are calibrated per sector based on pre-disaster I-O tables and assume constant returns to scale. Three different modes of inventory management are applied to different sectors: anticipatory based on expected orders, responsive based on receipt of orders, and just-in-time. The model makes an explicit distinction between losses that occur during the recovery period and prerecovery losses of a disaster that occur in the time period when the affected industries cannot recover yet because they are still inundated. This distinction is relevant for the application at hand because flooding in low-lying polder areas in the Netherlands can be of a long duration since water needs to be pumped out. Labor recovery is related to flood duration and how long it takes to make an inundated polder area accessible for labor, which is highly uncertain. Labor is assumed to have fully recovered within three months after the disaster, which can be viewed as an ad hoc assumption.

The results of the model by Koks et al. (2015) show that for high-probability floods, the direct losses are about twice the size as the indirect losses. Indirect losses are small for these flood types due to quick recovery periods. Indirect losses increase nonlinearly with direct losses and exceed direct losses for flood probabilities of one in four thousand or lower and are about 140 percent of the direct losses for an extreme one in ten-thousand-year flood. Uncertainty analysis shows that indirect losses are more uncertain for more extreme flood types, and this uncertainty is rightly skewed with a long right tail of the distribution into higher indirect losses. Expressed in annual expected damage or risk, the indirect losses are about 50 percent smaller than direct losses. Sensitivity analyses show that indirect losses decline especially with a faster reconstruction period, a more heterogeneous economic structure that is less dependent on the regional economy, a faster recovery of labor supply, and a larger supply of existing inventories by companies.

Another dynamic I-O model that examines disaster recovery periods and economic output losses has been developed by Santos et al. (2014). The model is applied to Tennessee’s Nashville metropolitan area, which is frequently hit by tornadoes and floods. They extend an I-O model with an event tree analysis to examine propagation of a disaster shock across interdependent economic sectors. Inoperability of a sector after a disaster is determined on the basis of unavailable workforce relative to workforce size for a sector. The model is calibrated using survey data of impacts of disasters with various intensities on workforce availability. A novelty of the inoperability I-O model is a dynamic adjustment of inoperability of a sector in response to a disaster, which allows for examining sector recovery periods and the impact of new perturbations. The event tree analysis determines in each period after the shock, in stages in a probabilistic way, whether a new positive or negative perturbation to output occurs or not and how this influences inoperability of a sector. This approach allows for evaluating effects of risk management strategies within the recovery period.

The model application by Santos et al. (2014) entails a simulation of three hypothetical disaster scenarios. Scenario 1 is a disaster that reduces the available workforce by half, limits operability of the utility sector by 80 percent, and takes thirty days to recover from. This causes a total economic loss of $472 million. Scenario 2 is similar except that an additional perturbation implies that the inoperability of the utilities sector persists for ten days, which has the result of increasing losses by $14 million, partly due to higher losses of sectors that are dependent on utilities. In scenario 3, a positive perturbation occurs due to good risk management, which allows the utility sector to recover after five days, an improvement over scenarios 1 and 2. Total economic losses are now $469 million, which implies savings of $3 million and $17 million compared with scenarios 1 and 2, respectively. This is an illustration of how the model can be used to evaluate risk management practices. Moreover, it can derive a ranking of economic losses for the different sectors for each scenario, which allows for identifying how vulnerable sectors are to disasters. The results show that the highest losses are incurred in service-oriented sectors, while manufacturing-oriented sectors score worst on inoperability after a disaster.

**B2. Multiregional I-O Modeling of Disasters**

Koks and Thissen (2016) built upon the study by Koks et al. (2015) by examining how a flood of the Rotterdam harbor affects economic activity in regions across Europe. For this purpose, they developed the Multiregional Impact Assessment (MRIA) model. The MRIA model is similar to the model in Oosterhaven and Bouwmeester (2016). It also shares certain features of the ARIO, such as the modeling of both supply-side and demand-side effects of a disaster and the accounting for supply-side constraints, but the dynamic adaptation process and price changes in ARIO are not part of the MRIA model. Nonlinear programming is applied to account for endogenous import and supply constraints in the optimization of a demand-determined model. To examine ripple effects of a disaster to multiple regions, it includes multiregional tradeoffs via trade links between the regions based on actual data of multiregional trade flows. In particular, the model estimates production losses in affected and other regions, increased production in nonaffected regions to substitute for lower production in the affected area and reconstruction needs there, and regional welfare distribution effects of increased production inefficiencies caused by the disaster. Although possibilities for input substitution are not accounted for, the model thus allows for substitution of production between regions, which is viewed as a resiliency measure. Moreover, it estimates inefficiencies that may be caused by substitution of companies that were more efficient before they were affected by the disaster to less-efficient companies outside of the area affected by the disaster. A dynamic modeling of the inoperability period of industries affected by the disaster and reconstruction demand drive the reconstruction phase of the model, which is determined by exogenous parameters; recovery is assumed to be completed after six months, one year, and two years for small, intermediate, and large floods, respectively.

The results show that the loss in supply in the region affected by the disaster can be taken over by additional supply in other regions, which explains the largest share of output increase in nonaffected regions, while a very small part of the increase is due to reconstruction demand. These substitution effects come at the expense of a large cost in terms of the use of less-efficient production technologies. Regions that import from the affected region generally suffer from the damaged production supply there, while export-oriented regions benefit because they take over part of the demand that cannot be satisfied by the affected region. Compared to the previously discussed studies by Koks et al. (2015) and Hallegatte (2008), the indirect losses as estimated by the MRIA model are significantly smaller than the direct losses. This can be explained by the substitution effects allowed for by the MRIA model between regions on the broader geographical scale, which dampen indirect effects of a disaster. This makes the outcome of this model more similar to flexible capital and labor movement in multiregional CGE models, as is shown in Koks et al. (2016). Sensitivity analysis shows that the assumptions made about the recovery period have a large influence on the results, with substantially larger indirect losses for longer recovery periods.

MacKenzie et al. (2012) developed a multiregional I-O model to examine indirect production losses due to disabled production facilities caused by the 2011 earthquake and tsunami in Japan. Their multiregional model connects all countries for which necessary data is available and the rest of the world based on international trade, using industry-level imports and exports. The model shows how a given level of demand in one or more countries generates production in a certain number of countries. The disaster enters the model through destruction of production facilities that are directly impacted by a disaster and through demand changes for goods of certain industries, such as those related to reconstruction. Moreover, companies can be impacted indirectly because of changes in production of industries that supply intermediate goods and services to companies directly impacted by the disaster. Suppliers are assumed to be uniformly distributed throughout the country, and indirect impacts of a disruption are assumed to be proportional between a country’s domestic production and the rest of the world’s imports. If direct impacts are unknown, then the model can also be estimated on the basis of total (direct and indirect) impacts on industries. Direct production losses in a country can be replaced with inventory or substitution by production in other countries, which limits negative impacts on satisfying demand. This substitution through imports is modeled by assuming that the fraction of imports from each country remains constant, while the size of total imports is increased to satisfy demand when domestic production is impacted by a disaster. Limitations to this substitution exist due to transportation costs, consumers not preferring the foreign-produced goods, and foreign suppliers being unwilling or unable to increase export. Moreover, countries not directly impacted by the disaster may substitute imports from the impacted country with increased domestic production. This would increase production in not directly impacted countries, while their production may decrease due to lower demand from industries in the impacted country.

MacKenzie et al. (2012) use data on Japanese industrial production for March, April, and May 2011 following the earthquake and tsunami, which is compared with 2010 business-as-usual production for assessing the direct disaster impacts on production and changes in monthly consumer sales and changes in final consumption. Total Japanese production losses exceeded $51.9 billion in March and April, which represents 7.3 percent of Japan’s total monthly output, and $20.7 billion in May. Direct production losses to all other countries than Japan were only $17.2 billion during these three months, of which China experienced most losses (namely, $3.5 billion). Inventories played an important role in limiting losses; by making up for lost inventories after recovery, Japan should recover $20.3 billion of initially lost production. When accounting for indirect impacts, the total economic losses in Japan and the other countries substantially decline— by about 40 percent—for example, due to increased reconstruction demands. In the three months following the disaster, total direct and indirect production losses in Japan are estimated at $78.1 billion and Japan’s GDP lost at $41.7 billion, which represents 3.6 percent of Japan’s normal economic output. The model can also rank losses for specific industries. This shows that the transportation and office equipment industry, which includes the automotive sector, experienced the largest losses in production, which results in high indirect production losses for the service and manufacturing sectors. Production losses that resulted from lower demand in March and April were less than a tenth of losses from disabled production, and in May, much of this lost demand was returned again. Increased imports from other countries and use of inventories limited consumption declines. In the three months following the disaster, Japan’s exports fell by 5 percent, which was mainly replaced by more domestic production in other countries. This increased domestic production in other countries exceeded their indirect losses due to disabled Japanese production facilities, meaning that the disaster in Japan had net macroeconomic benefits for these other nations.

**B3. Including Resilience and Assessing Vulnerability in I-O Models**

A handful of studies examined total economic impacts of a shutdown of ports, for example, due to terrorist attacks, bombing, or labor strikes (see Rose and Wei 2013 for a discussion of these studies). An interesting study of factors that can mitigate such losses and is also relevant for the natural disaster domain is done by Rose and Wei (2013), who augment a demand- and supply-driven I-O methodology to account for resilience. Resiliency factors in their application of a general disaster (including a natural disaster, like a hurricane) in sea ports in Texas entail the ability to mute impacts of a port disruption at the impacted site or along the supply chain. In particular, they examine the economic impacts of a ninety-day shutdown of the ports at Port ArthurandBeaumont in terms of import, export, and operations disruptions. Their model accounts for both supply- and demand-driven impacts following a disaster, and various modifications are made to the standard approach to account for resilience. Modeled resilience activities include ship rerouting, which applies to both imports and exports; export diversion, which entails using goods that would normally be exported to substitute for lacking import goods; use of inventories and the Strategic Petroleum Reserve for replacing oil imports; conservation of inputs in production processes that are lacking in supply; putting unused capacity to work; input and import substitution of disrupted supplies of production inputs; and production recapture to make up lost production when the port is back in operation through rescheduling of production.

The results of the indirect economic impacts of port disruptions without considering resilience measures estimated by Rose and Wei (2013) are $9.6 billion in terms of total regional output loss, which represents 53.9 percent of regional total gross economic output, and impacts rise to $12.9 billion and 72.5 percent of regional total gross economic output when onsite port disruptions are included. Applying all the resilience tactics can reduce regional losses by 78 percent and total losses by 68 percent. Of the resilience measures, shipping rerouting and production rescheduling have the greatest effects in mitigating regional output losses, and conservation and access to the Strategic Petroleum Reserve have the smallest. Moreover, import and export resilience tactics have a large potential for reducing total aggregate losses. Total impacts of the disruption of the ports for the entire US economy are $166.8 billion, of which 95 percent can be reduced through resiliency activities. This reduction is higher than the regional level reduction of resilience due to a higher effectiveness of import shipment rerouting and export diversion at the national level.

Another approach to include resilience in an I-O model is presented by Jonkeren and Giannopoulos (2014), who adapt a dynamic inoperability I-O model that is applied to a study of economic consequences of the failure of critical infrastructure caused by extreme winter storms in Europe. This model is called the Resilience Inoperability I-O model. Resilience is included through the following two main changes made to the standard model approach. First, the model augments the standard assumed recovery path of a concave up decreasing curve for infrastructure or an economic sector impacted by a disaster that assumes that recovery initially goes fast after the disaster but then slows down. In particular, the recovery path is made dependent on the kind of disaster and particular sector. For instance, directly impacted sectors may recover slowly in the time just following the disaster and faster afterward, while an indirectly impacted sector may follow the opposite (standardly assumed) recovery path. A numerical example shows that these different assumptions about the shape of the recovery path have a large influence on estimates of total economic losses (a difference of a factor 4.5). Second, the aspect of inventory as resiliency measure is refined in the adjusted model by interpreting it more broadly as any resiliency measure that allows for the continuation of supply of an industry or economic sector affected by a disaster. While earlier studies introduced inventory in this model framework as only delaying the disruptions in production, Jonkeren and Giannopoulos (2014) allow for inventories to compensate for both production losses due to directly damaged production capacities and disruptions caused by unavailable supply of inputs for the production process.

Jonkeren and Giannopoulos (2014) apply their Resilience Inoperability I-O model to a scenario of a winter storm in Europe that damages critical infrastructure. In particular, they focus on a scenario of storm damage in the Netherlands due to specific damages to airports, railways and rail stations, and roads as well as power outages and disruptions of telecommunications. Total economic losses for the Netherlands in this scenario are estimated to be €2.3 billion, which is about 0.4 percent of GDP in the Netherlands. In this case study, inventories have reduced economic losses by 31 percent compared to the loss that would occur without inventories. It should be noted that the model neglects cross-border economic impacts, which would be important for an open economy like the Netherlands’.

Yu et al. (2014) apply an inoperability I-O methodology to create indexes of a sector’s vulnerability to a natural disaster in the Philippines, where earthquakes and typhoons are common. Such an index can guide post-disaster risk mitigation policies, for example, by prioritizing sectors that should receive aid to limit indirect disaster losses to the economy. Vulnerability is defined as “the measure of a system’s capacity to absorb and recover from the occurrence of a hazardous event” (Yu et al. 2014), where a high capacity implies a low vulnerability, which is related to high resilience. In particular, the index of Yu et al. (2014) evaluates vulnerability on the basis of economic impact and propagation length of the disaster (diversity of reach of a sector through interconnectivity with other sectors) as well as sector size. Through the I-O methodology, the index depends on inter-sector linkages. The vulnerability index shows which sectors are most desirable for giving aid to minimize adverse inoperability impacts of economically significant sectors to the rest of the economy. The findings show that highly vulnerable sectors that should receive priority for aid and reconstruction after a natural disaster are manufacturing, private services and transportation, communication, and storage. A sensitivity analysis shows that private services are consistently a high-priority sector for aid, which fulfills an important function in ensuring the continuous operations of companies.

*Table B1. Summary of application, model features, and main findings of reviewed I-O studies of natural disasters*

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Application** | **Model features** | **Main findings of disaster impacts and mitigation factors** |
| Hallegatte (2008) | Hurricane Katrina | Adaptive regional input-output (ARIO) model | Total economic loss $149 billion; $107 billion is direct loss |
|  | Louisiana, USA | Includes sector production capacity limits | Total losses increase nonlinearly with indirect losses above $50 billion |
|  |  | Disaster impacts on both demand and supply | Sharp declines in employment and worsening of trade imbalances |
|  |  | Accounts for import substitution and price changes | Limited production capacities hamper reconstruction |
|  |  | Adaptive behavior in demand and supply | Important influence of overproduction and adaptation time parameters |
|  |  | Monthly time interval over a ten-year horizon |  |
| Koks et al. (2015) | Flood risk | ARIO model with the following main adjustments: | Expected annual indirect losses are about 50 percent of direct losses |
|  | Rotterdam harbor, Netherlands | Catastrophe model of capital and labor losses | Indirect losses increase nonlinearly with direct losses |
|  |  | Cobb-Douglas production functions per sector | Indirect exceed direct losses for flood events with probability <1/4000 |
|  |  | Impacts from both reduced labor and capital | Indirect losses are more uncertain for extreme flood events |
|  |  | Modeling pre-recovery period losses | Recovery period of labor supply is an important unknown parameter |
| Koks and Thissen (2016) | Flood in Rotterdam harbor | Multiregional Impact Assessment Model (MRIA) | Damaged production can be overtaken in nonaffected regions |
|  | Regions in Europe | Models production technologies and inefficiencies | Import-oriented regions lose; export-oriented regions gain |
|  |  | Nonlinear programming of supply constraints | Production substitution results in substantial technological inefficiency |
|  |  | Disaster impacts on both demand and supply | Indirect losses are smaller than direct losses due to regional substitution |
|  |  | Includes multiregional tradeoffs via trade links | Recovery time is an important unknown parameter |
|  |  | Allows for multiregional production substitution |  |
| MacKenzie (2012) | Earthquake and tsunami | Multiregional I-O model | Total direct and indirect production losses in Japan are $78.1 billion |
|  | Japan and rest of the world | Disaster impacts supply and demand | Indirect effect of reconstruction demand limits direct losses with 40 percent |
|  |  | Allows for inventory and import substitution | Japan lost $41.7 billion or 3.6% in GDP |
|  |  | Domestic production substitutes disrupted import | Inventories played an important role in limiting losses |
|  |  | Short-run focus on months following the disaster | Highest losses in transportation and office equipment industry |
|  |  |  | Consumption declines were limited due to imports and inventories |
|  |  |  | Other countries than Japan experienced net macroeconomic benefits |
| Rose and Wei (2013) | General disaster in harbors | Demand and supply I-O model with resilience measures: | Regional impacts can be as large as $13 billion |
|  | Texas, USA | Ship rerouting, export diversion, use of inventories | Resilience can reduce regional impacts by 70 percent |
|  |  | Use of Strategic Petroleum Reserve | National impacts amount to $166.8 billion |
|  |  | Conservation of inputs, production recapture | Resilience can reduce national impacts by 95 percent |
|  |  | Input and import substitution | Impacts are substantially smaller than studies not considering resilience |
| Jonkeren and | Storm | Resilient inoperability I-O model | Shape of recovery path influences economic losses with factor 4.5 |
| Giannopoulos (2014) | Europe | Shape of recovery path depends on disaster | €2.3 billion losses from critical infrastructure failure in the Netherlands |
|  |  | Inventory as a broad resilience measure | Inventories reduced direct and indirect production losses by 31 percent |
| Yu et al. (2014) | Earthquake or typhoon | Inoperability I-O model for vulnerability based on: | The vulnerability index shows which sectors are most desirable for aid: |
|  | Philippines | Economic impact and sector size | - Manufacturing, private services, transportation, communication, storage |
|  |  | Propagation length of the disaster | - Given uncertainties, a consistent high-priority sector is private services |
| Santos et al. (2014) | Floods and tornadoes | Dynamic inoperability I-O model | Disaster without additional shocks causes $472 million in losses |
|  | Nashville, USA | Event tree analysis of shocks | Additional negative shock utility sector increases losses by $14 million |
|  |  | Negative or positive perturbations in recovery path | Risk management utility sector saves losses between $3 and $17 million |
|  |  | Allows for examining recovery periods | Highest losses are incurred in service-oriented sectors |
|  |  | Evaluates risk management within recovery period | Manufacturing-oriented sectors score worst on inoperability |

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**ONLINE APPENDIX C: COMPUTABLE GENERAL EQUILIBRIUM MODEL STUDIES OF NATURAL DISASTERS**

This appendix describes several studies of integrated catastrophe and CGE modeling, large-scale CGE models, and resiliency measures in CGE models, which are summarized in Table C1.

*C1. Integrated Catastrophe and CGE Modeling and Spatially Detailed CGE Models*

Tsuchiya et al. (2007) developed a spatial CGE model that estimates the economic impacts of transport infrastructure disruptions caused by hypothetical Tokai-Tonankai earthquakes in Japan. A transportation model that includes interregional freight and passenger flows is integrated in the multiregional CGE model of fourteen zones, which estimates how commodity flows and business trips (an input factor) change due to the earthquakes. Different earthquake scenarios cause disconnections in transportation networks, which increases transportation time and costs and results in a new market equilibrium in the CGE model. The CGE model estimates a short-run equilibrium by assuming that labor, capital, and their prices cannot adjust in the short run, while commodities and their prices can change between regions.

The total transport-related losses of Tokai-Tonankai earthquakes are estimated to be 18.5 billion yen per day, which are felt in all the eastern and western regions of Japan. The large majority of losses (up to 70 percent) occurs in the three largest metropolitan areas. Losses increase nonlinearly when multiple transportation nodes are disrupted, which points toward interaction effects. In a worst-case scenario, when multiple key transportation nodes are disrupted, losses can increase up to 36.4 billion yen per day. If railroads and expressways would be upgraded, then 16.3 billion yen per day of the total worst-case scenario cost can be saved.

Pauw et al. (2012) combine a hydrometeorological crop loss model with a regional CGE model to estimate economic losses of droughts and floods for Malawi, which heavily depends on rainfed agriculture. The hydrometeorological crop loss model is a catastrophe model type that estimates direct costs of droughts and floods in terms of crop losses. In particular, it is a stochastic model that captures the full distribution of extreme weather events. These direct crop losses enter the CGE model as reduced crop productivity and land availability for farming caused by droughts and floods, which reduces agricultural production and changes equilibrium prices and factor resources. This again impacts household income. The CGE model assumes that once crops are planted, a farmer cannot switch to more drought- or flood-resistant crop types if an extreme event occurs. Specific loss mitigation or resilience measures are not explicitly modeled or evaluated. Agriculture is divided into eight agro-ecological zones, urban areas, and three sizes of farms. Moreover, the CGE model is linked to a microsimulation module, which, based on survey data, measures changes in the distribution of household incomes and poverty that result from the economic effects of droughts and floods.

The main result of Pauw et al. (2012) is that at least 1.7 percent of GDP in Malawi is lost annually due to the combined effects of droughts and floods. Depending on the severity of a drought, losses per event range from 1.1 percent up to 18.8 percent of GDP. The most severely affected crop types are maize and tobacco. Falling crop production has negative indirect effects on a variety of sectors, including livestock, food, and transport processing. The worst affected are small-scale farmers in the south of the country who depend heavily on maize production. Broader macroeconomic effects entail an increase in agriculture imports, a worsening of Malawi’s current account balance, and a depreciating exchange rate, which results in a small increase in industrial output. On a household level, poverty increases as a result of a lack of food, lower incomes, and higher prices. This effect is especially severe for nonfarm households and small- and medium-scale farmers. Model results are broadly consistent with an experienced drought in Malawi in 1993 and 1994. However, the authors note that such a comparison with modeled and observed impacts is complicated by a variety of factors; for example, economic structures (like the share of agriculture in GDP) change over time; factors other than floods and droughts determine observed impacts, like changes in world commodity prices; model outcomes depend on a selection of a base year of “normal conditions” of no policy or weather shocks, which is difficult to identify in reality.

Carrera et al. (2015) developed an integrated framework of a spatially detailed catastrophe model that estimates property damage from a flood of the Po River that occurred in Italy in 2000, the results of which feed into a CGE model that assesses indirect economic impacts. The CGE model is a regional one based on the Global Trade Analysis Project (GTAP) (Narayanan and Walmsley 2008) that is calibrated for the north, center, and south of Italy while accounting for international trade relations and has a one-year time scale. The output of the property damage estimates from the catastrophe model enter the CGE model as the damage to (as a percentage reduction) available primary production factors (capital, land, and labor) per sector, which shocks the economy. Next, changes in factors’ productivity are estimated based on the assumed duration of impacts to production factors per sector. Impacts on labor are estimated at a municipality level and flooded land for spatially detailed land use classes, which are translated into total economic impacts per sector in the north of Italy depending on the location of these sectors. The model does not account for inventories, subsidies, and post-disaster reconstruction. Two recovery scenarios are modeled. First, a rigid model does not allow for factor endowments to move among the three Italian regions, and substitution possibilities among the regions are limited. Second, a more flexible model allows for capital and labor mobility within Italy and for more substitution possibilities among the Italian regions than across countries. The model output is the yearly disruption of regional and sectoral output and related real GDP.

Direct losses based on the catastrophe model approach are estimated to be between €3.3 and €8.8 billion (in 2000 values). Estimated indirect losses are in between €647 and €1955 million, which is between 19 and 22 percent of direct losses. The direct flood impacts occur in the north, where large indirect losses are also observed, which are partly offset with small economic gains in the not directly affected areas in the center and south of Italy, assuming the flexible recovery scenario results in higher indirect losses in the north. However, this flexible scenario also results in higher positive effects in central and south Italy due to positive substitution effects and an inflow of capital and labor from the north, which are negligible in the rigid scenario. The most-affected sectors in the north, which are grains and crops, and livestock meat products, are the same sectors that experience positive production effects in central and south Italy. Estimated economic impacts outside of Italy for the European Union or rest of the world are negligible. Empirical validation of these results using actual productivity effects caused by the 2002 Po River flood is infeasible due to data limitations (Carrera et al. 2015).

**C2. Large-Scale CGE Models**

Several large-scale CGE models have assessed the economic consequences of sea level rise. Deke et al. (2001) examine this at a global scale using a dynamic CGE model but focus on only the cost of coastal protection. In this model, the cost of protection reduces investment and, hence, lowers the capital stock and economic output. Estimated GDP losses of a thirteen-centimeter sea-level rise forecast are small and range between 0.3 percent for India and 0.006 percent for Western Europe. Darwin and Tol (2001) apply a static global CGE model called FARM that is partly based on GTAP to assess the cost of sea-level rise without coastal protection and with optimal coastal protection, which results in a loss of productive capital. They estimate that the annuitized total cost of fifty centimeters of sea-level rise in 2100 amounts to $66 billion for the world, which reduces to $4.4 billion if optimal coastal protection is implemented. Total economic cost of the latter scenarios are, with $4.9 billion, slightly higher. A more recent study that considers a broader range of sea-level rise effects is done by Bosello et al. (2012), who estimate the economic impacts of sea-level rise and related flood risk for Europe using a CGE model called the GTAP-EF model. The direct economic impacts of sea-level rise that enter the CGE model are first estimated with the DIVA model. The latter model estimates at a subnational spatial resolution how sea-level rise results in erosion, flood risk, and inundation; changes in coastal wetlands; and surface salinization. The GCE model estimates impacts of these direct effects in terms of land lost and adaptation costs on GDP, investment, and trade flows. In contrast to the other two sea-level rise studies, Bosello et al. (2012) also account for the induced demand for coastal protection, which is modeled as an additional investment and is still costly since it is financed with lower consumption.

The model estimates small land losses from sea-level rise between 0.002 percent in Finland and 3.5 percent in Greece, with the exception of Malta, which loses 12 percent of its land. This loss of land as a production factor increases the price of now-scarcer land input and the price of land-intensive goods, which reduces GDP between 0.0003 percent in the Netherlands and 0.08 percent in Malta. In seven EU countries, positive GDP effects are observed, which range between 0.009 percent for Sweden and 0.005 percent for Cyprus, which attract investment due to relatively higher capital returns and experience trade benefits as a result of relative price changes. More positive effects occur in the more developed economies, where factor substitution possibilities are relatively higher. The economic costs are substantially smaller in an optimal coastal protection scenario. The optimal protection cost can be very high for some countries (e.g., $ 44.5 billion for the United Kingdom), but it also fosters investment in countries with vulnerable coasts, which stimulates the construction sector. GDP impacts under optimal protection are mixed: eleven countries gain (between 0.008 percent in the United Kingdom and 0.8 percent in Denmark), and the other countries slightly lose (between −0.01 percent in Poland and −0.54 percent in Finland).

**C3. Including Resilience in CGE Models**

A standard CGE model that is calibrated using historical data reflects only business-as-usual conditions and, hence, does not capture the full range of resilience tactics that business can apply to limit disaster impacts. Several studies have adjusted CGE models to explicitly model such resilience measures. Rose and Liao (2005) developed a CGE model with recalibrated production function parameters of the elasticity of substitution and productivity to reflect resilience. This is done using survey data of resilience responses adopted by companies during the Northridge earthquake and region- and context-specific simulation results of output losses following earthquakes. The model is applied to a case study of a disruption of the Portland Metropolitan Water System caused by an earthquake. Water is explicitly modeled as an input in the production functions, which allows for estimating economic impacts of disruptions in water supply. Flexible production functions are specified that reflect resilience in a sense that disrupted inputs, like water, can be substituted to a certain degree by other inputs. Moreover, adaptation in an emergency situation is accounted for by allowing for changes in production function parameters, which, for example, reflect more-efficient water use than under normal conditions, the use of backup (water) supplies, increased substitutability of production inputs, and long-run changes in production technologies. The CGE model estimates that the total economic loss for the region is $1.122 billion, caused by a four-week disruption of water supply under a business-as-usual scenario (assuming no mitigation). Indirect losses are 22 percent of direct losses. This scenario does allow for water conservation and substitution; not accounting for these resiliency responses would increase indirect losses up to 90 percent of direct losses, which shows the high benefits of these responses. Total output losses can be limited to $627 million when risks are mitigated by replacing cast-iron pipes before the earthquake.

Rose et al. (2016) developed a CGE model to estimate the regional, state, and national economic consequences of a tsunami in Southern California, measured in terms of reduced GDP. Such a tsunami would, for example, cause disruptions of ports, marina-related sectors, and the fishing industry, which affect the wider economy. The CGE model analyses (i) the immediate business interruption losses caused by physical destruction of facilities and production units and evacuation; (ii) economic indirect impacts of lost production in industries upstream and downstream of the directly affected sectors while accounting for price and quantity changes; (iii) the influence of various resilience tactics on these impacts. These resilience measures include rerouting shipping from damaged port facilities to other ports, diverting exports for substituting for disrupted imports, input conservation and substitution, using inventories by customers of disrupted ports, relocating activities within a port, and working overtime or extra shifts when the port reopens.

Overall tsunami losses in California are much smaller than those experienced in Japan during the 2011 tsunami because tsunamis along the California coast cause lower waves and less inundation than in Japan. Without accounting for resiliency measures, the following losses are expected to result: total direct losses related to a two-day disruption of ports are $2,396 million for all of California, and direct building, content, and marina slip damages along the Californian coast are $1,948 million in total. The total of these damages is dominated by the disruption of imports and building content damages. Direct port-related impacts in Southern California are about twice the size as damages to the rest of California. These direct impacts can be substantially reduced by static resiliency measures that use existing resources more efficiently, especially through the use of inventories. As an illustration, resiliency measures reduce economic damages from import disruptions from $987 million to $29 million for all of California, and this reduction is from $210 million to $153 million for the impacts of export disruptions. Without resiliency measures, total economic impacts on GDP are $3.1 billion for all of California, which represents 0.323 percent of annual GDP. About half of these losses are caused by import disruptions. The model also estimates which industries are most affected, which are manufacturing industries due to disruptions in imports and exports. The main resilience measures for reducing indirect losses are production and sales recapture at a later date; these measures reduce the total impacts from import and export disruptions and evacuation between 80 and 85 percent, which is on top of the aforementioned resilience tactics that reduce direct impacts. Moreover, Rose et al. (2016) integrate the CGE model results in an I-O model of the US national economy to examine national GDP impacts of the tsunami in California. Estimated total GDP impacts on the US economy are $10 billion without the resiliency measures, which reduces to $0.6 billion with the resiliency measures. This is mainly due to recapture of trade disruptions and production recapture after property damage occurred. A limitation of the model that Rose et al. (2016) point out is that the static CGE model cannot capture well the economic recovery process and the role that insurance payments can play in facilitating recovery.

*Table C1. Summary of application, model features, and main findings of reviewed CGE studies of natural disasters*

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Application** | **Model features** | **Main findings of disaster impacts and mitigation factors** |
| Tsuchiya et | Earthquake | A spatial CGE model of fourteen zones | Total transport-related losses are 18.5 up to 36.4 billion yen per day |
| al. (2007) | Japan | Integrated transportation model | Losses are felt in all the eastern and western regions of Japan |
|  |  | Earthquake disconnects transport networks | Losses mainly occur in large metropolitan areas |
|  |  | Disruptions of commodity flows and business trips | Losses rise nonlinearly with multiple transportation disruptions |
|  |  | CGE estimates short-run equilibrium effects | Upgrading railroads and expressways saves 16.3 billion yen per day |
| Pauw et al. | Drought | Linked hydrometeorological crop and regional CGE model | At least 1.7 percent of GDP in Malawi is lost annually |
| (2012) | Flood | Catastrophe model type estimates direct impacts | Losses per event range between 1.1 and 18.8 percent of GDP |
|  | Malawi | Direct agriculture losses and wider economic effects | Negative indirect effects occur in a variety of sectors |
|  |  | Microsimulation of impacts on income and poverty | Worst affected are small-scale farmers |
|  |  | Comparison of results with real drought events | Droughts worsen income inequality and poverty |
|  |  |  | Model results are broadly consistent with experienced drought |
| Carrera et | Flood | Integrated catastrophe and regional CGE model | Direct losses are between €3.3 and €8.8 billion |
| al. (2015) | Po River | Direct flood impacts estimated on a local level | Indirect losses are between €647 and €1955 million |
|  | Italy | Direct flood impacts reduce production factors | Losses occur in the north and gains in central and south Italy |
|  |  | Rigid scenario limits factor mobility and substitution | Regional imbalance in impacts is higher in the flexible scenario |
|  |  | Flexible scenario of factor mobility and substitution | Impacts outside of Italy are negligible |
| Darwin and | Sea-level rise | Static global CGE model called FARM | 50-cm sea-level rise in 2100 causes direct costs of $66 billion |
| Tol (2001) | protection | Scenarios without and with optimal coastal protection | These costs reduce to $4.4 billion with optimal coastal protection |
|  | World | Protection investments reduce productive capital | Total economic costs under optimal protection are $4.9 billion |
| Bosello | Sea-level rise | Integrated catastrophe and large-scale CGE model | Land losses generally range between 0.002 and 3.5 percent |
| et al. (2012) | flood risk | Directs effects are land lost and protection costs | Land losses raise prices of land input and land-intensive goods |
|  | Europe | Indirect impacts on GDP, investment, and trade flows | GDP losses are between 0.0003 and 0.08 percent |
|  |  | Coastal protection increases investments | Seven countries have higher GDPs |
|  |  |  | Optimal coastal protection substantially reduces economic costs |
| Rose and | Northridge | CGE model that accounts for resiliency tactics | Without mitigation, total economic costs are $1.122 billion |
| Liao (2005) | Earthquake | Focus on disrupted water supply after earthquake | Indirect losses are 22 percent of direct losses |
|  | USA | Water is a separate input in production functions | Indirect losses are 90 percent of direct losses without resiliency tactics |
|  |  | These functions reflect a range of resiliency tactics | Replacing cast-iron pipes can mitigate total losses to $627 million |
| Rose et al. | Tsunami | CGE model that accounts for resiliency tactics | Without resilience, direct California losses from ports are $2.4 billion |
| (2016) | California | CGE estimates regional and state-level effects | Direct impacts along the Californian coast are $1,948 million |
|  |  | Integrated I-O and GCE models for national effects | Without resiliency, total GDP losses are $3.1 billion for California |
|  |  | Direct impacts on ports, fishing, and marina sectors | Resilience limits import disruption cost from $987 to $29 million |
|  |  |  | Resilience limits export disruption cost from $210 to $153 million |
|  |  |  | Production and sales recapture limits losses up to 85 percent |
|  |  |  | US GDP losses are $10 billion without and $0.6 billion with resilience |

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**ONLINE APPENDIX D: EMPIRICAL STUDIES OF THE DIRECT AND INDIRECT ECONOMIC IMPACTS OF NATURAL DISASTERS**

This appendix describes in more detail the data and empirical methods underlying the empirical studies of the economic impacts of natural disasters.

**D1. Data sources of Dependent and Independent Variables**

The primary database for identifying natural disasters at the global scale is the Emergency Events Database (EM-DAT) compiled by the Centre for Research on the Epidemiology of Disasters (CRED) from various sources, including UN agencies, NGOs, insurance companies, research institutions, and press agencies.[[5]](#footnote-5) The EM-DAT data generally pertains to direct damages and contains the location and outcome of disasters, such as the number of people killed, injured, affected, and made homeless by a disaster, the area affected, the total estimated damages, and impacts on some sectors. A disaster is included in EM-DAT if one of the following holds: ten or more people are killed; one hundred or more people are affected; a declaration of a state of emergency is issued; a call for international assistance is made. A key advantage of the EM-DAT data is that it is publicly available and perhaps more transparent compared to the other global databases. However, EM-DAT has been criticized for including many small disasters due to its flexible inclusion criteria and for inaccuracies, such as the recording of (uncorrected) damage estimates from local authorities that are often inflated shortly after a disaster. Such inaccuracies may depend on the economic and political conditions in a country, possibly leading way to endogeneity bias in the studies that utilize the EM-DAT data. Similar databases such as NatCatSERVICE[[6]](#footnote-6) and Sigma,[[7]](#footnote-7) created by the reinsurance companies Munich Re and Swiss Re, have also been used in the literature, although less frequently since they are not broadly publicly available.

A growing branch of the literature studies the economic effect of hurricanes. Instead of using the EM-DAT data, these papers rely on databases maintained by NOAA (for the United States) (see, e.g., Strobl 2011) or on reconstructed wind field of cyclones in the International Best Track Archive for Climate Stewardship (IBTrACS) database (see, e.g., Hsiang and Jina 2014). This approach, proposed first by Hsiang (2010), accounts for both the location and intensity of wind forces at the 0.1° x 0.1° resolution for more than 6,700 storms over the period 1950–2008. This provides an especially useful measure of the physical strength of hurricanes at the country-year level that is grounded in climate physics. Another promising approach is the method proposed by Felbermayr and Groschl (2014) for constructing indices from geophysical or meteorological variables such as storms, floods, earthquakes, and extreme temperature.

**Outcomes**

The wide range of possible direct and indirect impacts of disasters is evident from the observed large range of economic outcome data studied in the literature. These include GDP, GDP growth rate, trade flows, death counts, employment, per capita income, expenditures, migration, housing and other asset values, and government transfers. The most commonly studied outcomes, GDP and GDP growth (which is a more relevant outcome for studies of the long-term impact of disasters), are measured using the Penn World Tables or the World Development Index and are generally analyzed as a country-year panel data. Several studies also focus on disaster-related mortality as an outcome, using the data available in the EM-DAT database.

**Disasters**

The literature based on the EM-DAT database generally aggregates different disasters occurring in a country-year into a single index. In particular, most researchers use an unweighted sum of the various disaster measures. For example, the index could be a count of all earthquakes, floods, landslides, storms, and extreme temperature occurring in a country-year and normalized by land area. Other studies focus on individual disasters, such as specific hurricanes, on constructed measures of physical intensity, like wind speeds, or on impacts, like the share of affected or killed population.

**Controls**

The list of control variables used in the literature is also extensive, reflecting the many different types of economic outcomes that have been studied. Country-level studies of disaster effects on GDP or GDP growth rates generally control for population and land area (size of the economy), baseline income levels, income inequality, average education, political regimes, development of financial system and institutions, measures of openness to trade, and foreign direct investments. Some studies control for weather and/or climate variables as those can also affect economic indicators. Furthermore, some climatic variables are themselves correlated with the probability of natural disasters (e.g., cyclones and surface temperature). A remaining challenge in the literature is to control for changes in location-specific vulnerability to disasters over time, because time series of vulnerability-related indicators like stringency of building codes or disaster preparedness is often not available (Estrada et al. 2015). Moreover, the impact of many natural disasters (e.g., floods, hurricanes, and earthquakes) tends to be highly localized (i.e., cities or neighborhood within cities), and so future studies should aim at constructing correspondingly highly granular local economic impact variables to obtain better measures of the impacts of disasters. To this end, some recent studies proxy local economic activity using nighttime light data (Bertinelli et al. 2016).

**Mitigating Factors**

An important component of the literature studies the factors that can mitigate the economic and social effects of natural disasters (or characterize vulnerability to natural disasters). Early studies tended to focus on the role of income (GDP) or economic development as a factor mitigating the damages associated with natural disasters (see, e.g., Kahn 2005). Most studies indeed find that higher-income countries suffer less indirect economic damage, although the relationship appears nonlinear (Kellenberg and Mobarak 2008). Other mitigating variables include average education levels, openness to trade, and political and institutional factors (such as better institutions and democratic regimes), which also contribute to reducing natural disaster impacts.

*D2. Econometric Methods*

Most estimates of the economic impact of natural disasters are based on regressions of macroeconomic variables (e.g., GDP growth) measured at the country level on some measure of disasters, such as the number of disasters, the monetary damages, or the number of fatalities. The earlier literature used primarily cross-sectional regressions to measure such effects (e.g., Skidmore and Toya 2002):

1. Yc = α + βDc + γXc + uc

where *Yc* is an economic outcome for country (or location) *c*, for example, the growth rate of GDP in country *c* over a given period of time. The variable *Dc* is an indicator for the occurrence of a natural disaster in country *c*. As discussed above, many studies use country-level data from EM-DAT to construct *Dc*. The vector *Xc* includes control variables, in particular determinants of growth. The parameter of interest is *β*, which captures the effect of disasters on the economic outcome *Yc*. A central problem in the estimation of equation (1) is that it is likely to be biased for several reasons. Omitted variable bias will arise if there are important determinants of the economic outcomes under study that are not included in the model and correlated with the disaster measures. For example, reporting of the disaster measures may depend on the socioeconomic and political attributes of a country, some of which are difficult to quantity with data.

As a result, almost all of the reviewed papers make use of panel data aggregated to country-year level. Studies focusing on the United States alone similarly use panel data aggregated to the county-year level. The typical panel regression model is of the form:

1. Yct = α + βDct + γXct + λc + ηt + uct

where *Yct* is a measured economic outcome for location *c* in year *t*. The variable *Dct* is an indicator for the occurrence of a natural disaster in location *c* in year *t*. As described above, the literature has considered a wide range of measures for natural disasters, including hurricanes, total number of disasters, and disaster-related mortality (which is also sometimes used as an outcome). Importantly, the relationship between disasters and economic outcomes can be dynamic, and so some studies allow for lagged effects in *Dct* to enter the model. A key advantage of panel data is that they allow for the inclusion of country-fixed effects (*λc*), which control for all time-invariant country-specific unobserved determinants of the outcomes. For example, the location-specific fixed effects can help control for the effect of difficult-to-quantity attributes of a location, such as ambient hazard risks, geographical features, culture and norms, and institutions. The year-fixed effects (*ηt*) will control for global shocks leading to changes in the outcomes over time. Many studies will augment the year-fixed effects with region-specific year-fixed effects and/or country-specific trends to better control for location-specific changes in economic policies that affect the outcomes.

*Table D1. Summary of application and method, data sources, and main findings of reviewed empirical studies of natural disasters*

|  |  |  |  |
| --- | --- | --- | --- |
| **Study** | **Application and methods** | **Main data sources** | **Main findings** |
| Kahn (2005) | Cross-country OLS regressions; zero-inflated negative binomial models; cross-sectional regressions (i.e., without country-fixed effects) for seventy-three countries, balanced over 1980–2002 | Outcome: deaths from natural disasters (EM-DAT); main predictors: geographical features, institutions, and income (Penn World Tables) | Likelihood of natural disasters is uncorrelated with national income.  Countries with higher GDP per capita suffer fewer deaths per natural disaster. Countries with higher income inequality (Gini index), lower population density, and democratic regimes also suffer fewer deaths per natural disaster. |
| Felbermayr and Groschl (2014) | Panel data regressions including country- and year-fixed effects for 108 countries, unbalanced over 1979–2010 | Outcomes: occurrence and intensity of natural disasters (EM-DAT), GDP growth rate (Penn World Tables); main predictors: various natural disaster indicators (author’s GeoMet data, EM-DAT, and NatCatService), indicators for types and intensity of natural disasters (GeoMet); mitigating factors: Degree of democratization, trade and financial markets’ openness (various sources) | Likelihood of natural disasters of a given physical magnitude being included in EM-DAT depends on country GDP per capita.  Natural disasters (defined on the basis of physical indicators) reduce GDP growth rate. Effect is nonlinear in disaster intensity.  Degree of democratization, trade openness, and financial markets openness reduce the negative effect of disasters on economic growth. |
| Hsiang (2010) | Panel data regressions including country- and year-fixed effects for twenty-eight Caribbean-basin countries, unbalanced over 1970–2006 | Outcomes: GDP per capita by country and for seven industrial sectors (National Account Statistics, United Nations); main predictors: cyclone trajectory and intensity, defined as local energy dissipated per square meter (HURDAT Best Track database, reconstructed to country-year using Limited Information Cyclone Reconstruction and Integration for Climate and Economics [LICRICE] model), surface temperature (NCEP-NCAR Climate Data Assimilation System I), and rainfall (Climate Prediction Center Merged Analysis of Precipitation [CMAP]) | Statistically insignificant effect of cyclones on total GDP per capita  Negative effect of cyclones on GDP in agricultural, wholesale, and retail trade (including tourism-related income), and mining sectors  Positive effect of cyclone on GDP in construction sector |
| Anttila-Hughes and Hsiang (2011) | Panel data regressions including province- and year-fixed effects for households in the Philippines for the years 1985–2008 (unbalanced); household-level controls are included in the regressions. | Outcomes: household-level assets, income, and consumption for 1985–2006 (various years, from the Family Income and Expenditure Survey [FIES]), infant mortality rate for 1993–2008 (various years, from the Demographic and Health Survey [DHS]); main predictors: typhoon trajectory and intensity, defined as wind speed in seconds per meter (International Best Track Archive for Climate Stewardship [IBTrACS] database, reconstructed to province-year using Limited Information Cyclone Reconstruction and Integration for Climate and Economics [LICRICE] model) | Typhoons reduce household incomes and destroy assets, measured by electricity access, toilets, TV, and “strong walls.”  Reductions in household income due to typhoon lead to expenditure reductions in many categories, including health and human capital investments.  Typhoons increase female infant mortality rate but not male infant mortality rate. |
| Strobl (2011) | Panel data regressions including county- and year- fixed effects for 409 US coastal counties in the North Atlantic Basin region | Outcome: per capita income growth rate (Bureau of Economic Analysis); main predictors: constructed hurricane destruction index based on a monetary loss equation, local wind-speed estimates derived from a physical wind field model, and local exposure characteristics (HURDAT database, processed using the HAZUS model) | Average hurricane reduces county-level personal income growth rate in year of exposure, with no significant lagged effects.  Hurricane exposure leads to out-migration of higher-income individuals from the affected county. |
| Leiter, Oberhofer, and Raschky (2009) | Panel data regressions for firm-level outcomes including industry, country, and year-fixed effects | Outcomes: firm-level employment, value-added and total assets (AMADEUS database); main predictors: flood events (EM-DAT) | Firm total assets and employment increase following a flood.  Firm productivity (measured by value-added) is not statistically significantly related to flood exposure. |
| Skidmore and Toya (2002) | Cross-sectional regressions for eighty-nine countries, with outcomes averaged over 1960–1990 | Outcome: GDP growth rate (Penn World Tables); main predictors: natural disaster occurrence (from Davis [1992] and EM-DAT), including climatic (e.g., floods and hurricanes) and geologic (e.g., earthquakes) disasters | Geologic disasters are positively correlated with GDP growth rates, and climatic disasters are negatively correlated with GDP growth rates.  Growth effects are explained by TFP channel. |
| Hsiang and Jina (2014) | Panel data regressions including country- and year-fixed effects for 110 countries, unbalanced over 1970–2008 | Outcome: GDP growth rate (Penn World Tables); main predictors: cyclone trajectory and intensity, defined as wind speed in seconds per meter (International Best Track Archive for Climate Stewardship [IBTrACS] database, reconstructed to province-year using Limited Information Cyclone Reconstruction and Integration for Climate and Economics [LICRICE] model) | Cyclones have large negative and persistent effects on GDP growth rates: a one-meter-per-second increase in wind-speed exposure today leads to about half a percent GDP reduction fifteen years later.  Negative effects of cyclone on output detected for total output, as well as output in agriculture, services, and industry  Impacts are smaller for countries that experience cyclone activity more frequently. |
| Noy (2009) | Panel data regressions including country- and year-fixed effects for 109 countries, unbalanced over 1970–2003 | Outcome: GDP growth rate (World Bank World Development Indicators); main predictors: natural disaster damage index, calculated from reported monetary damages and onset month (EM-DAT); mitigating factors: literacy, institutional strength, characteristics of financial markets (various sources) | Natural disasters reduce GDP growth rates, with larger impact in smaller, less-developed countries.  Countries with better institutions, literacy rates, and higher openness to trade and government spending suffer smaller GDP growth losses per disaster. |

**References Appendix D**

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1. Ramsey (1928) shows that under standard neoclassical assumptions on utility, a constant saving rate is the utility maximizing choice. [↑](#footnote-ref-1)
2. The reverse can also happen. A disaster can help an economy escape the poverty trap. Some have, for example, argued and provided evidence that the Black Death in Europe, a disaster that eliminated almost 50 percent of the population while leaving the capital stock and fertile land untouched, was a trigger for the industrialization that followed. See, e.g., Van Zanden (2009). [↑](#footnote-ref-2)
3. Institutional quality is usually measured by having experts evaluate the institutional contexts at the country level. These surveys of opinions are then combined into indices that capture some dimension of institutional quality, like protection of property rights, corruption, or effectiveness of government. It is not hard to imagine that these experts will weigh the actual economic performance of these countries in their assessment of the institutional quality. [↑](#footnote-ref-3)
4. This formalization adds little to our discussion here. See Capello (2015) for an accessible discussion of these models. [↑](#footnote-ref-4)
5. http://www.emdat.be/. [↑](#footnote-ref-5)
6. https://www.munichre.com/en/reinsurance/business/non-life/natcatservice/index.html. [↑](#footnote-ref-6)
7. http://institute.swissre.com/research/overview/. [↑](#footnote-ref-7)