Repeated Natural Disasters and Poverty in Island Nations: A Decade of Evidence from Indonesia.

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ABSTRACT

Natural disaster impact is not altogether determined by nature but rather contingent upon the economic conditions of the receiving community. This research provides selective evidence of the impact of natural disaster risk on long-term poverty rates. By estimating a decadal panel of Indonesian household data, we complement existing static poverty analyses with a dynamic perspective. By using expected consumption as our measure of welfare, we focus on changes to both the distribution and the level of consumption from natural disaster shocks in addition to other sources of aggregate and individual risk. Aggregated to the country level, we find that natural disaster risk is (i) disproportionately impacting consumption-constrained households, (ii) increases projected poverty rates and (iii) economic development factors such as income, urbanization, and institutional strength determine natural disaster losses at the country-level.

INTRODUCTION

Globally, natural disaster events and losses are escalating (see Figure 1). Since 1970, natural disasters have affected more than 5 billion persons globally with over 1 trillion US$ in financial losses (Centre for Research on Epidemiology of Disasters, 2011). The human-built environment (for example, the pattern of human settlements) and economic conditions (for example, quality of infrastructure) of an economy foreshadow natural disaster vulnerability (Linrooth-Bayer and Amendola, 2000; Lucas, 2001; United Nations Development Programme, 2004; Kahn, 2005; Strömberg, 2007; Vigdor, 2008). Repeated natural disaster events on island nations, such as Japan's 2011 disaster trifecta (earthquake, tsunami, and nuclear disaster) or Haiti's 2010 earthquakes catalyzing a tertiary cholera disaster, hearken the need for improved research on recurring natural disasters on islands. Using a decade of household-level data from 1997 – 2007, we show that frequent, repeated natural disaster shocks do not impact households uniformly. Rather, the ex-ante microeconomic conditions of the household portend disproportionate impact to resource-constrained households.

LITERATURE

Economic development and natural disaster risk are not independent: often the poorest persons are the worst affected by environmental shocks. While wealthier nations experience greater absolute financial losses, poorer nations suffer greater relative financial losses (as a percentage of gross national product) and more human losses: nearly 90% of disaster-related deaths and 98% of persons affected by disasters between 1991-2005 occurred in developing nations, with more than 25% of these deaths occurring in the least developed countries (World Bank, 2010b). Disaster damage is not only primary; secondary losses from disaster include decreased human

capital, depleted savings, and long-term implications on economic development and growth (Easterly and Kraay, 2000; Rasmussen, 2004; Hoddinott, 2006; Toya and Skidmore, 2007; Carter et al., 2007; Vigdor, 2008).

Regional and global disaster vulnerability studies revealed the higher structural[1] vulnerability of island developing states. Characterized by their economic size (for example, limited natural resource endowments, high import content, small domestic market and dependence on trade markets), insularity and remoteness (for example, high per-unit transport cost and supply uncertainty), and proneness to weather hazards, island nations are especially vulnerable to the effects of climate change, sea-level rise, and weather hazards (Intergovernmental Panel on Climate Change, 2007). Population and economic development pressures have increased this risk.

Island developing states suffer the greatest magnitude of natural disaster damage, both in terms of financial losses (percentage of gross national product) and human losses (percentage of population affected) (Noy, 2009). Between 1970-1989, islands represented over half of the countries (13 of 25) with the greatest number of natural disasters (United Nations Conference on Trade and Development, 1997). Island developing states have higher relative exposure to many economic and natural hazards and illustrate the intricate human-environment relationship of vulnerability: the high extent of coastal geography increases event likeliness and small scale, dwindling risk-abatement and consumption smoothing options. Islands face unique constraints from their remoteness and size, such as limited choices in risk diversion and consumption smoothing mechanisms. Increasing population density and urbanization exacerbate

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[1] Structural vulnerability manifests from exposure to natural or external hazards whereas vulnerability in general manifests from economic and environmental factors interacting with hazards (Cutter, 2001).

these constrictions. The United Nations International Strategy for Disaster Reduction (United Nations International Strategy for Disaster Reduction, 2009) finds that disaster risk is highly condensed in poorer countries with weaker governance. In tandem, Kahn's (2005) study of 57 nations demonstrated that countries with greater wealth and stronger institutions experience less vulnerability to natural disasters.

At the household level, economic development pressures are forcing increasing numbers of households to locate in relatively riskier areas: flood plains, on earthquake faults, or below sea level; unsafe dwellings exacerbate natural disaster risk. Overwhelmingly, these risky areas are within urban areas. Over 50% of global populations reside in urban areas and is increasing with time[2]: 2.9 billion persons (48%) lived in urban areas in 2001 and estimates project 4.9 billion persons (60%) will live in urban areas by 2030 (United Nations Habitat, 2008). New urbanites demand housing, infrastructure, and services such as sanitation. Rapid urbanization cannibalizes post-disaster smoothing options, such as own-food production and water sanitation. The mutually dependent relationship between the poor and their environment is obvious within the rural context: livelihood depends upon public good provision from natural resources (for example, forests offer food and kindling resources, rivers offer fish and irrigation resources) yet obtuse within the urban context. Urban poor lack access to public good resources both in the natural and human-planned environment, the former of which has been a priori expended by the process of urbanization.

Poverty impacts the probability of suffering from a weather hazard - poverty may dictate that individuals locate in riskier areas, increasing their probability of loss from

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[2] Most global population growth between 2001 and 2030 will be in urban areas with rural areas having nearly static population levels (UN-Habitat, 2008).

weather hazards[3]. Poverty measures have been used throughout the economics literature as a welfare gauge of the less endowed (Ligon and Schechter, 2003; Foster et al., 1984), yet many measures and estimators present in the vulnerability to poverty literature omit welfare consequences of risk. Risk has important consequences on consumption levels and individuals will try to look for ways to smooth their consumption streams in order to maintain a constant level of well being. The consensus of existing research on shocks in developing countries is that transitory shocks seldom translate into permanent fluctuations in consumption – that is, households are able to smooth their consumption over time in the presence of transitory shocks. This is because households have developed a variety of coping mechanisms, such as depleting household assets or borrowing, increasing family labor supply, and reducing investments in health and education.

Economic development and disaster management research is experiencing a shift from examining poverty through a static (consumption) lens towards understanding disaster losses as a function of economic development, integrating poverty reduction programs with natural disaster and environmental management, especially in urban areas[4]. This research contributes to the understanding of how natural disaster risk impacts poverty. Appealing to the poverty-vulnerability relationship described as different sides of the same coin, long panel data permits us to investigate not only these

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[3] For example, an urban poor person may live in a tin shanty house more susceptible to cyclone winds compared to their wealthier neighbor living in a concrete house: even though they both face the same risk from the weather hazard, their vulnerability, or likelihood of suffering a loss, differs.

[4] For example, the Bangladesh Urban Disaster Mitigation Project aims to improve the capacity and risk management in urban areas.

relationships but enhances understanding of the causal directionality of these relationships.

DATA

We directly follow Ligon and Schechter (2003) in defining vulnerability to poverty as a positive probability of expected utility from consumption falling below a relative threshold[5]. We apply the Ligon and Schechter measure to the case of Indonesian households experiencing long-term increases in weather hazards and natural disaster rates. Using Rand's Indonesian Family Life Surveys (IFLS) rounds 2 (1997), 3 (2000) and 4 (2007), we estimate the LS measure for 3269 households over 10 years.

Indonesia, the world's 4th most populous country, has a unique geography, demography, and economic environment spanning the equator and Pacific and Indian Oceans. The Republic of Indonesia is the world's largest archipelago with a total land area of 1,919,317 km^2 exposed to a plethora of natural disasters, especially related to seismic activity (volcanoes, earthquakes and tsunamis). Indonesia has a high extent of mountainous territory and a climate characterized by two seasons: dry (June – September) and rainy (December – March).

Indonesia is classified as a low-middle income developing country (World Bank, 2010a) and an island developing state by the United Nations. Indonesia has a market-based economy and is a global emerging market with dependence on oil export revenues. The Indonesian currency is the Rupiah (Rp). In 2010, Indonesia's gross domestic product (labor force) had the following sectoral decompositions: 14.4%

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[5] We could have alternatively chosen to set a specific threshold, such as the poverty line. Since we are interested specifically in population-relative estimates, we use a population-relative threshold for within-population comparisons.

(42.1%) agriculture, 47.1% (18.6%) industry, and 38.5%(39.3%) services (Central Intelligence Agency, 2010). The major agricultural products are timber, rubber, rice, palm oil, and coffee. Indonesia's major exports are within the energy industry, including oil, natural gas, palm oil (crude), and coal. In terms of quality of life, the average life expectancy at birth is 71 years and the adult[6] literacy rate is 92% (World Bank, 2010a).

Indonesia suffered an economic crisis (part of the Asian Financial Crisis) beginning in mid-1997 during which the government intervened and then a financial crisis in late 2005 attributed to international oil prices. The poverty impacts of the 1997 financial crisis have been discussed in the literature: while poverty rates increased dramatically from 12.4% to 24.5% between 1997 to 1999, the rates returned to between 13.1 – 14.2% by 2002 (Suryahadi et al. 2003). In 2006, 17.8% of the Indonesian population lived below the international poverty line, ranking 69th in the world. The Gini index was 39.4 in 2005 and Indonesia is ranked 108th (as a medium development country) in the 2010 Human Development Index.

Our main data source is longitudinal survey data drawn from the Indonesian Family Life Survey (IFLS), a survey of households and communities in Indonesia. Our empirical application uses three rounds of the survey: IFLS2, conducted in late 1997, IFLS3, conducted in 2000, and IFLS4, conducted in 2007 (we do not include information from IFLS2+ which sampled only 25% of IFLS households specifically assessing the impact of the Asian financial crisis). While numerous researchers have used the survey data to estimate impacts of financial and health shocks, this is the first study to our knowledge to use this data to estimate the impact of natural disasters on vulnerability to

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[6] People aged 15 and older.

poverty. The IFLS surveys include a plethora of household information including consumption (expenditures and own-produced), assets, livelihood and employment, assets, demographic information (age, sex, education level), and household decision-making. Rational expectations and the belief that (research) advances should rest on an enhanced empirical understanding of how households respond to economic and physical environments and on the role of government policy in shaping those environments directly influenced the IFLS survey design (Deaton, 1997).

IFLS is representative of 83% of the Indonesian population, surveying individuals in 13 of the 27 providences. Households were assigned a unique 7-digit household id number in round 1 (1993) that was maintained for each survey wave in rounds 2, 3 and 4. This allowed merging across waves to obtain a data set containing only those households that participated in each round of the survey for a total of 3269 households with complete information for our selected variables. We restore random sampling by applying household weights to account for both attrition and full population representation. Table 1 defines the variables used in this study.

The 3269 households tracked for 10 years have an average household size of 6.03 members, with an average of 1.03 workers and 0.38 pensioners per household. The average head of household is aged 56.4 years old with 19.1 years of education. 33.5% of the heads of households were female and 53% of households reside in rural areas. IFLS contains detailed consumption information by item, food and non-food, including items purchased and own-produced and their price in time t. Our consumption variable was constructed by summing total food consumption (in Rp), purchased and

own-produced, by household. We use consumption in price times quantity, rather than just quantity, to account for heterogeneity of purchasing power across space[7].

Indonesia is located on an arc of volcanoes and fault lines known as the "Ring of Fire;" the country is prone to recurrent seismic activity with approximately 400 total (150 active) volcanoes. Many volcanoes are located on the most densely populated island, Java. Indonesia has a long history of natural disaster shocks. In 1883, the Krakatoa (Krakatau) volcano erupted causing a tsunami to strike Western Java and Southern Sumatra, resulting in over 36,000 deaths (Dasgupta, 2010). Tsunami waves engulfed coastal towns and villages within 2 hours of the eruption; some villages were swept away with the tide as parts of the Krakatau island submerged with the implosion of the volcano. One hundred and twenty one years later, an earthquake just off the coast of Sumatra (Sumatra-Andaman earthquake) caused the 2004 Indian Ocean tsunami. Over 225,000 people were killed with Indonesia accounting for 73% of the tsunami-related deaths (Centre for Research on the Epidemiology of Disasters (EM-DAT), 2011).

During the period of our analysis, Indonesia suffered 145 natural disasters with an average of 13 disasters per annum. Floods were the most frequent disaster type, accounting for 31.7% of the natural disasters between 1992-2007, followed by earthquakes (24%), and wet mass movements[8] (18%). Table 2 presents Indonesia's disaster losses from 1997-2007.

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[7] Consider the case of urban versus rural prices: if the price of one kilogram of rice is 100 Rp in the urban area and 50 Rp in the rural area and both households consume one kilogram of rice, including only quantity would imply that the households are consuming the same amount. Including prices would indicate that the urban household has greater consumption.

[8] Includes avalanches, landslides, and debris flows.

The most costly form of natural disaster during the study period was wildfire, accounting for 47% (9,315,800 in 2000 US$) of the financial losses, followed by earthquakes, accounting for 43% (8,652,600 in 2000 US$). While floods were the most frequently experienced natural disaster, they only accounted for 8% of the financial losses. However, in terms of deaths caused by natural disasters, earthquakes account for 95.8% (173,639 of the 181,086); the 2004 earthquake-tsunami accounted for 165,816 (95.5%) of these deaths.

Natural disaster household experience was included in each round of IFLS. Households were asked to recall a 5-year history of shocks, including natural disasters and weather events. We include this household-level information as a dummy variable = 1 if the household reported a natural disaster or weather shock causing an economic disturbance in their household (= 0 otherwise). In round 2 (1997), 2.3% of surveyed households reported experiencing a natural disaster shock in the last 5 years, in round 3 (2000), 1.9% of the surveyed households reported experiencing a natural disaster shock in the last 5 years, and in round 4 (2007), 21.2% of the surveyed households reported experiencing a natural disaster shock in the last 5 years. Across the panel, 11.5% of the surveyed households experienced a natural disaster disturbance. Table 3 presents evidence of natural disaster persistence: households who experienced a disaster shock in one period were 155% more likely to experience a second disaster shock compared to households who did not experience the first disaster disturbance.

Rodrik (2004) emphasizes the need for good instruments – those with sources of exogenous variation, which are an independent determinant, not a consequence of,

poverty. For this reason, data scarcity and measurement error[9], and following the economic development literature, we not use survey-reported income as our measure of income but rather follow Filmer and Pritchett (2001) by constructing a housing quality index as our measure of income. We construct A_t^i as household i's housing quality in time period t:

$$A_t^i = \frac{f_{1t}}{s_{1t}}\left(a_{i1t} - a_{1t}\right) + ... + \frac{f_{Nt}}{s_{Nt}}\left(a_{iNt} - a_{Nt}\right)$$

where

f_{1t} = scoring factor asset 1 *in year t*
a_{i1t} = i^{th} household value for asset 1 *in year t*
a_{1t} = sample mean for asset 1 *in year t*
s_{1t} = sample s tan dard deviation for asset 1 *in year t*
$\mu_A = 0$ *by construction*

The assets for household i ($a_{i1\text{-}14}$) include the type of dwelling, number of rooms, type of flooring, roof and walls, size of house and yard, presence of waste, trash or stagnant water, ventilation, whether the kitchen is inside or outside, presence of a stable and whether household members sleep in the same room as the kitchen. Higher values of the index indicate higher housing quality.

We include the total amount of Rupiah in savings reported by the household as a form of self-insurance (dissavings) available to households. In times of economic shocks, households dissave to smooth consumption. Savings are especially important to households when market mechanisms stifle other forms of self-insurance (such as borrowing or transfers).

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[9] For our final estimated sample of N=10887 (n=3269, t=3) we have 559 observations with reported income and 10328 missing observations.

Home ownership is a major asset for many households. It offers both security and liability during economic shocks, especially within the natural disaster context. We include a dummy variable to indicate whether one or more members of the household own the home they reside in. Home ownership may offer security in the form of households having a place to live, land ownership and alleviating the need to pay rent. On the other hand, within the disaster context, home ownership implies households must rebuild their shelter if destroyed by the storm – the home may be a liability in that repairs may be costly or materials to rebuild may be unavailable. Further, there may be a relationship between evacuation and homeownership. It has been documented through post-disaster qualitative interviews that some homeowners are reluctant to evaluate for fear of looting.

We also include a dummy variable to indicate if a household has animals. Animals offer many consumption-smoothing benefits such as potential income (from selling the animal, selling their offspring, or selling by-products such as eggs or milk), potential labor (using the animal for traction), or food (consuming the animal). Akin to the motivation above regarding home ownership, the risk-relationship may reverse at the individual level as animal ownership represents greater household resources exposed to risk.

We include the number of pensioners per household as a form of self-insurance. The pension serves as guaranteed income to the household; this is salient in the disaster context as other paid labor – formal and especially informal – may be interrupted by the disaster's impact. Consider two forms of employment as examples. If a worker is a formal agricultural laborer and the disaster decimated the crops or land,

this individual faces a great possibility of losing their income. If a worker rather is an informal entrepreneur (for example, they sell clothing at a local market which they make at home) and the disaster decimates the local community, this individual faces a great possibility of losing their income stream as a result of other household's not being able to afford their goods or services. In both cases, having a pensioner in the household will offer stable income during the shock time. In the self-insurance context, a pension is a certain, known transfer.

The set of k-observable household variables includes household head characteristics of sex, age, age^2, employment status and level of education; household characteristics of residential type (urban or rural), region of the household, household size and household self-insurance mechanisms (housing quality (proxy for income), asset ownership, savings and pensioners) and reported natural disaster shock experience. Table 4 presents the summary statistics for variables used in calculating the consumption estimates, the vulnerability to poverty measure and correlates of the vulnerability measure.

CALCULATING VULNERABILITY TO POVERTY

The first step in calculating the vulnerability to poverty measure was obtaining the fitted consumption estimates ($\widetilde{c}_t^i$) by regressing log-consumption on the set of individual risk variables (x_t^i), household fixed effects (α^i) and year fixed-effects (η_t). Results of this regression are presented in Table 5 and Table 6 presents the summary statistics for $\widetilde{c}_t^i$. The highest attainable level of $\widetilde{c}_t^i$ is 1 and the average for the sample over the timeframe is 0.50. The fitted consumption estimates, $\widetilde{c}_t^i$ are used to calculate each

household's average consumption ($\overline{\overline{c^i}}$) and their expected consumption for each period

($E(\widetilde{c}^i_t)$). The expected consumption estimates are used in the risk measurements

($EU^i\left[E(\widetilde{c}^i_t|\overline{x}_t)\right]$, $EU^i\left[E(\widetilde{c}^i_t|\overline{x}_t,x^i_t)\right]$, and $EU^i\left[E(\widetilde{c}^i_t)\right]$). Second, we select the "poverty

line" as population relative. By defining the poverty line, $\overline{c}$, as 1, households with

average predicted consumption, $\overline{\overline{c^i}}$, less than 1 are considered in current poverty. The

final step ahead of estimating the vulnerability measure was assuming CRRA risk

preferences.

RESULTS

Table 7 presents the vulnerability to poverty measure estimates in the top row and

correlates to the measure in the rows below. The interpretation of the vulnerability

measure is direct, given our consumption normalization: the vulnerability measure

represents the population average percentage utility loss resulting from the presence of

poverty and risk (row 1 column 1) as the sum of current poverty (row 1 column 2),

aggregate risk (row 1 column 3), idiosyncratic risk (row 1 column 4) and unexplained

risk/measurement error (row 1 column 5).

The utility of the average Indonesian household sampled is 62% lower than it

would be in the absence of consumption risk and inequality, assuming costless

redistribution. In terms of consumption risk, aggregate risk is the greatest form of risk

faced by Indonesian households and the greatest contributor to vulnerability to poverty

in Indonesia. This is partially attributable to their island scale – for example, small size,

limited resource base and limited spatial scale to smooth aggregate risk. It is also

partially attributed to their strong social insurance programs smoothing individual risk[10] and household's ability to self-insure their risk through savings and assets. While aggregate risk includes macroeconomic shocks such as financial or currency crises in addition to natural disasters, our results demonstrate that natural disaster risk is impacting household consumption decisions through the highly significant correlations of household natural disaster experience and the various components of vulnerability to poverty. Indonesia suffers recurrent natural disaster shocks and households with greater self-insurance mechanisms (savings and assets) and greater levels of human capital (education) are coping with these repeated shocks better than less endowed, less educated households.

Aggregate risk is the greatest form of risk faced by Indonesian households and increases a household's future probability of being in poverty. It accounts for nearly 40% of the vulnerability to poverty measure (aggregate risk comprises 24.68 of 62.4%). Compared to the magnitude of aggregate risk's contribution to future poverty in Bulgaria, Indonesian households face much greater aggregate risk. We expected this result of living on an island exposed to extreme weather events. In accordance with poverty trap findings of Carter et al. (2007) and Hoddinott (2006), the inability to consumption smooth leads to natural disaster shocks sending households near the poverty line into poverty. Interestingly, we find current poverty status roughly equal in magnitude to the impact of aggregate risk on future poverty rates. This is a very important result for island communities such as Indonesia who tout decreasing poverty

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[10] For example, Indonesia had health insurance and food subsidy programs available to households during the time frame.

levels as economic development; yet their long-term economic development – in terms of the poverty lens – is being hampered by aggregate risk.

We find current poverty status to be smaller than LS, contributing 40% to vulnerability to poverty (they found current poverty status accounted for 57% of vulnerability to poverty in Bulgaria). Idiosyncratic risk is small but highly significant, accounting for less than 1% of vulnerability to poverty. Unexplained risk (and potential measurement error) accounts for 13% of vulnerability to poverty. Our estimate of unexplained risk is much lower than Ligon and Schechter's (32%). This was expected as we took significant investment to find high quality, detailed household information, use a proxy rather than reported income and included more idiosyncratic controls in x_t^i as compared to Ligon and Schechter (2003) thus do not have as many unobserved sources of idiosyncratic risk as Ligon and Schechter (2003) (their estimate of unexplained risk was greater in magnitude than both aggregate and idiosyncratic risk). We also attribute this result to our inclusion of observed household-level shocks and numerous insurance-type mechanisms (while Ligon and Schechter include only number of workers, pensioners and income level, we additionally include savings and some assets[11]).

There are some important caveats in comparing our results from Indonesia with results from Bulgaria. First and most importantly, we use a decade of household information (from 1997 to 2007) to analyze consumption smoothing whereas Ligon and Schechter use one year (1994 with 12 monthly observations) of household information. Appealing to the need for longer-term analysis as articulated by Ligon and Schechter,

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[11] Ligon and Schechter include animal, but not home ownership and do not include savings.

the scope of our analysis is much more long-term and thus captures enduring coping more so than Ligon and Schechter. Whereas their conclusions regarding household vulnerability to poverty reflect how households cope in the short-term with risk, our conclusions shed light on how households are coping over longer time horizons with frequent shocks, especially natural disaster shocks. Second, Bulgaria is a European nation comprised of one single landmass, exposed to one coast (the Black Sea) with much lower geographic risk of natural disasters. During 1994, Bulgaria experienced zero natural disasters; in 1993, they experienced one storm disaster with zero reported deaths, zero reported financial losses and 5000 persons affected (EM-DAT). Therefore, comparisons of our results with Ligon and Schechter's should be tempered by differences in time horizons and geographic natural disaster risk, the latter strengthening our case for differences in natural disaster vulnerability on islands.

There are notable differences between rural and urban households with respect to risk and poverty rates. Urban households face greater overall vulnerability to poverty and current poverty rates. Yet, rural households face a great deal more idiosyncratic risk than their urban peers. This is partially attributed to the distribution of resource levels: urban areas have better access to credit markets and greater human resource levels compared to rural areas. For example, housing and land values are higher in urban areas; food prices are often higher as well. The result is also partially attributed to the distribution of common-pool and public goods: in rural areas, there are more common-pool and public goods available at the aggregate level to smooth consumption. For example, while an urban household must rely on the formal market to purchase their consumption bundle (water, food, fuel), a rural household may rely on many

common-pool and public good resources available as rural amenities. These amenities may include fishing waters, sources of fuel for cooking, and fresh water sources. While rural aggregate risk is smaller, their individual risk is much greater as they do not have individual access to many insurance-type mechanisms integrated into the formal economy. For example, aid distribution and labor market opportunities are greater in urban areas. If we consider the case of a household suffering the loss of their home dwelling to a disaster, the urban household faces greater aggregate risk of secondary impacts (for example, disease outbreak) but lesser individual risk (for example, loss of income) than their rural peers. The urban household has access to temporary shelters, but lack access to individually sustain their provisions of basic needs (such as shelter, food and water) at the aggregate level as rural households do. Aggregate risk is less correlated with consumption shortfalls in rural households. Yet rural residence is correlated with higher levels of individual risk implying urban and rural households face different risk from interactions of their local environment.

EXPLAINING VULNERABILITY TO POVERTY

Subsequent to calculating the vulnerability to poverty measure, we estimate a linear regression of each component of vulnerability on the average household characteristics to identify correlates of vulnerability to poverty and the within components, mirroring Ligon and Schechter (2003). The overall sample mean of household characteristics are used as the independent variables in the regression in addition to household and time fixed-effects (for sample averages of these characteristics, refer to the summary statistics in Table 4). By identifying coping correlates, we offer a deeper understanding of how natural disaster risk impacts future

poverty rates and how consumption-constrained households are coping with permanent upswings in natural disaster rates.

Household natural disaster experience is highly correlated with the vulnerability measure and is time-sensitive to the conditions of the economic environment. While household disaster experience in the early 1990's (between 1992-1997) significantly increases vulnerability to future poverty (by nearly 68%), households who experienced a disaster shock during the late 1990's (between 1995-2000) are 36% less vulnerable to poverty. The timing of natural disaster shocks matter as they interact with the economy upon strike. Considering Indonesia's economic and political history during this timeframe reveals support for our findings. Indonesia's President Suharto is considered the most corrupt leader of all time (Transparency International, 2004); he was in power from 1968-1998. Indonesia rebounded from the Asian financial crisis in 1997, attributed by many to the government's intervention and social protection schemes available to households (between 1995 – 2005) and has steadily improved their institutional strength in the post-Suharto era (after 1998)[12]. During this time, government assistance was available for poor households and thus households were able to recover from disaster shocks riding on the coattails of interventions to alleviate the financial crisis (for example, there was a very beneficial rice subsidy program).

Households with savings are 43% less vulnerable to future poverty compared to households without savings. The presence of savings indicates the household is able to smooth their consumption intertemporally in the presence of shocks. Consistent with findings from across the world, self-insurance mechanisms decrease the likelihood of

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[12] For example, a common measure of institutional strength is the corruption index.

shocks acting as poverty traps. Not only do we find that households with savings are overall less likely to be in poverty in the future, they are also 88% less likely to be in current poverty and are better able to smooth consumption in the presence of aggregate risk (by 12%). Another self-insurance mechanism we examined was the number of pensioners in the household. As pensions continue to provide household income even during economic disturbances, they are often a consumption-smoothing safety net to recipient households. Households with pensioners are more than 25% less vulnerable to poverty than households without.

Animals offer consumption-smoothing benefits to households. Animals serve as a potential source of income (by selling the animal), labor (by using the animal to work fields), or as a consumable (food). Households with animals were 33% less vulnerable to poverty than households without animals.

Larger households are 16% more vulnerable to future poverty. Interestingly, sex of the female headed-households is significantly correlated with lower vulnerability to poverty and lower current poverty status. This suggests strong gender institutions in Indonesia. Reflecting on country statistics presented earlier, Indonesia has strong institutions reflected in successful crisis interventions (for examples, Asian crisis of 1997, oil crisis of 2005), alleviating food and price market frictions (for example, a rice subsidy) and the availability of heath care and insurance (for example, Kartu Sehat and Dana Sehat are available to households). In 2005, Indonesia's gender-related development index was ranked 94th, yet their human development ranking was only 107th.

Households in rural areas face 25% less current poverty than households in urban areas. Over the time period studied, Indonesia faced very volatile commodity prices[13]. These price volatilities impact households with greater reliance on purchasing (rather than own-producing) their consumption needs. Urban households are often more reliant on purchasing their commodities. In Indonesia, rural agriculture has significantly reduced rural poverty (Suryahadi et al., 2009). Supporting our findings regarding rural areas, the headcount of rural households living at the poverty line has been declining from 21.8% in 2006 to 16.6% in 2010 (World Bank, 2010a).

Households with self-insurance accruals are able to cope with aggregate risk better than households without self-insurance available. These self-insurance mechanisms decrease aggregate risk by presenting households with the ability to smooth their consumption losses in the presence of aggregate risk.

Urban households face greater aggregate risk compared to rural households, a result we attribute to not only characteristics of urban areas in general (higher agglomerations of resources, for example) but also the risk-proneness of where Indonesia's urban areas lie spatially. Recall Indonesia's historic experience with seismic activity and their geography: Jakarta, the most dense urban area in Indonesia is located on the island of Java, the most densely populated island in the world. Java is also located on the "Ring of Fire" chain of volcanoes. Their increased aggregate risk is a result of the interaction of geographic characteristics and locational decisions of millions of households. The choice to locate in the higher risk areas only serves to exacerbate the aggregate risk of the area. Urban and rural areas present different aggregate and

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[13] For example, domestic prices, especially food (increased by 118%), skyrocketed in 1998 with 78% inflation (Surhahadi and Sumarto, 2003).

individual levels of risk: urban areas are correlated with greater aggregate risk while rural areas are correlated with greater individual (household) levels of risk. We explain this as a result of differences in the levels and distributions of resources to smooth consumption. Urban areas present greater overall resource levels, especially formal market goods and services, which implies more to lose (recall that risk emerges from volatility of consumption). Further, the households are much more dependent on the formal market in urban areas compared to rural areas, especially with respect to labor, food consumption (purchased not own produced), and health. Yet, rural areas ex-ante offer different resource provisions: as the aggregate services and market integration are less in rural areas, there is less aggregate risk but greater individual risk. There are not as many individual-level smoothing mechanisms for households to smooth their losses. In the presence of a natural disaster shock, informal risk sharing is not fully effective (Sawada and Shimizutani, 2007). As urban households have significantly greater rates of savings and better access to borrowing (as a result of greater market integration), urban households have less individual risk to future poverty than their rural peers.

Natural disaster experience is a significant and negative correlate of individual risk for both the first (1992-1997) and last (2002-2007) time periods. This is the only component of our vulnerability measure that is significantly correlated with disaster experience in the last period. Households that experienced a disaster shock between 1992-1997 face lower idiosyncratic consumption risk. Yet, households with 1992-1997 disaster experience are also correlated with higher levels of aggregate risk and current poverty. This suggests that these households are better able to smooth consumption against risk individual to their household, but not able to smooth consumption in the

presence of aggregate risk (risk common to all). Interestingly, disaster experience from 2002-2007 is significantly (negatively) correlated only with individual risk. Global and national support for recovery from the 2004 tsunami explains the negative correlation with individual risk: households were able to defray this risk with exogenous recovery support.

Households with disaster experience in these two time periods are correlated with lower individual risk, offering some evidence that households may learn from natural disaster experiences. By experiencing a household-level disaster disturbance, a household may glean new information regarding natural disaster risk and impacts. This information may be used to rebuild stronger, thwarting future consumption losses from future natural disasters. For example, consider a household living on the coast. During a natural disaster, the household is directly impacted by a tsunami disaster. After this experience, the household may gain information on how to increase their self-protection in the future (perhaps they consider building a house on stilts or migrating further inland). Adding further credibility to these significant correlates, these results are consistent with our assumption of rational expectations.

Animal ownership is correlated with lower vulnerability to poverty, lower current poverty status, and lower aggregate risk (perhaps suggesting a relationship with wealth level). Yet, it is correlated with higher individual risk. This reflects the nature of assets in crisis times: they present the household with increased resources exposed to risk but importantly offer households an asset which may be used to smooth their consumption in the presence aggregate risk (animals are negative correlated with aggregate risk). Animal ownership represents a consumable resource, as households may directly

consume them or indirectly consume their value by selling the animal. As a source of guaranteed income, households with a pension recipient have a safety-net level of income available to their household in times of crisis. As this is also the time when the labor market may be disrupted causing income disturbances for households, pensions guarantee a minimum (certain) level of consumption for the household.

Greater levels of education attained by the household head are correlated with lower vulnerability to poverty, lower current poverty and lower aggregate risk but have no bearing on individual risk. For example, a more educated head of household may have improved access to (or understanding of) information on aggregate risk, such as forecast information or self-protection information. However, this information has no bearing on individual shocks, such as a health shock. The magnitude of the correlation is much smaller in aggregate risk as compared to overall vulnerability to poverty and current poverty status reflecting the permanent impact of human capital investments. Increased education levels have more salience in staving off poverty and future poverty as compared to coping with aggregate risk. This may be evidence that more educated heads of households have better information regarding aggregate risk and thus make better decisions regarding this risk. For example, these heads of household may have more information regarding disaster history or regarding geographic risk (such as fault line information), reflected in better household decision making (for example, building a house on a less risky plot of land).

CONCLUSIONS

We apply the Ligon and Schechter poverty measure to analyze Indonesian household vulnerability to poverty, with a focus on assessing aggregate risk impacts of

natural disasters. The decomposable measure shed light on the impacts of aggregate risk to future poverty rates in the long-term by estimating a 10-year panel of representative households. This research contributed to research needs identified by Ligon and Schechter whom called for longer panel data to extend their inferences. Further, as this measure employs a utilitarian framework, the impact of sources of risk on household welfare are more accurately represented as compared to the FGT-class of poverty measures, which, as noted by Ligon and Schechter (2003), detrimentally underestimate risk-reducing schemes such as self-insurance. Our results contribute additional evidence that shocks, such as natural disasters, affect expected poverty (Ravallion, 1998) and that poor households are less well (consumption) insured than their wealthier peers (Jalan and Ravallion, 2001). Natural disasters, as unexpected, aggregate shocks, can have a significant influence on the relatively poor household's welfare, including poverty inducement and persistence (Carter et al., 2007).

Indonesian households face risk, the greatest form of which is aggregate risk. As aggregate risk is not locally diversifiable, governments and policy makers alike require enhanced understanding of welfare impacts of this form of risk and how it impacts future poverty rates. We found that certain households are able to diversify risk through consumption smoothing over time. For example, receiving a pension offers a permanent, expected transfer payment, especially important for negative risk realizations such as natural disasters.

Social planners and policy makers seeking to decrease natural disaster losses should acknowledge the poverty consequences of increased risk from natural disasters and seek policies empowering households to minimize this risk, as this will also

implicitly decrease risk at the aggregate level. By estimating correlates of coping with this risk, our conclusions offer insights into household behaviors that decrease consumption risk. Policies promoting self-insurance mechanisms at the household level, such as household savings, decrease natural disaster risk at the aggregate and household levels. Self-protection mechanisms decrease the likelihood of a loss and are very important in coping with natural disasters, especially at the country-level as increased self-protection decreases aggregate risk. Appealing to our results regarding urban versus rural risk, governments seeking to decrease natural disaster risk should publicly disseminate information regarding high-risk prone areas to improve household expectations of long-term risk associated with their locational decisions. For example, public information regarding fault zones may improve household settlement decision-making.. Publicly available education on survival skills, such as swimming, will increase self-protection available to households.

The ex-ante conditions of an economy impact a household's ability to cope with a natural disaster shock. During spells of economic turmoil, natural disasters exacerbate suffering as coping mechanisms (for example, savings) are already strained. We demonstrated that households are less able to cope with natural disaster shocks during less favorable economic times (in the middle to late 1990's), yet are more able to cope in times of greater social protection and improving macroeconomic indicators (late 1990's through 2007). Households living on island nations are especially sensitive to these macroeconomic conditions. Indonesian households benefiting from their strong and improving economy, though not all households reap the same benefits. Households with low endowments of assets (housing, animals), human capital (education), and self-

insurance mechanisms (savings, pensioners) are the most vulnerable to poverty because they cannot smooth their consumption in the presence of aggregate risk. As macroeconomic conditions are more favorable in Indonesia as compared to small island developing states with much lower resource and wealth endowments, Indonesia is a good example of an island nation coping with increased natural disaster risk concurrent with improving economic conditions.

Table 1 Description of variables

Household characteristics	Description
Household size	Number of members in the household
Food consumption	Annual purchased and own-produced food consumption (quantity x price$_t$)
Residential type	Dummy variable; =1 if reside in rural area and =0 if reside in urban area
Age	Age of head of household, in years
Pensioners	Number of household members receiving a pension
Natural disaster	Dummy variable indicating if the household reported a natural disaster disturbance during the last 5 years
Education, < primary	Dummy variable = 1 if head of household has less than primary school completion; = 0 otherwise
Education, primary	Dummy variable = 1 if head of household has primary school completion; = 0 otherwise
Education, secondary	Dummy variable = 1 if head of household has secondary school completion; = 0 otherwise
Education, post-secondary	Dummy variable = 1 if head of household has post-secondary school completion; = 0 otherwise
Housing quality	Housing quality index (higher values indicate better quality); function of 14 housing-related characteristics
Employed	Head of household formal employment (= 1 if formally employed)
Sex	Head of household sex (=1 if female; = 0 if male)
Savings	Reported amount of total household savings, in Rp
Homeowner	Dummy variable = 1 if household owns; = 0 otherwise

Table 2 Total natural disaster losses from 1997-2007

Natural Disaster Type	Total number of disasters	Total people affected	Total people killed	Total damage (US$ '000)
Drought	1	1080000	672	89000
Earthquake	35	4939893	173639	8652600
Epidemic	19	133650	2892	0
Flood	46	3009810	2568	1612900
Mass movement wet	26	332325	1065	115004
Storm	2	3715	4	0
Volcano	11	125845	3	0
Wildfire	7	34470	243	9315800
Total	145	9659708	181086	19785304

(source: EM-DAT)

Table 3 Persistence of household natural disaster shocks.

	No Disaster$_t$	Disaster$_t$	Total
No Disaster$_{t+1}$	6291 (88.56%)	813 (11.44%)	7104
Disaster$_{t+1}$	128 (83.12%)	26 (16.88%)	154
Total	6419 (88.44%)	839 (11.56%)	7258

Table 4 Summary statistics

Variable		Mean	Standard deviation	Minimum	Maximum	Observations	
	overall	6.22	(2.51)	2.00	22.00	N	10887
Household size	between		(2.34)	2.00	18.33	n	3629
	within		(0.91)	-1.45	13.55	T	3
Residential type	overall	0.55	(0.50)	0.00	1.00	N	10887
(= 0 urban = 1 rural)	between		(0.20)	0.00	1.00	n	3629
	within		(0.45)	-0.12	1.22	T	3
	overall	54.64	(16.02)	16.00	115.00	N	10887
Age, household head	between		(15.26)	24.33	104.33	n	3629
	within		(4.87)	23.64	84.98	T	3
Pensioners	overall	0.38	(0.49)	0.00	2.00	N	10887
	between		(0.14)	0.33	1.67	n	3629
	within		(0.47)	-0.62	1.38	T	3
	overall	0.01	(0.09)	0.00	1.00	N	10887
Natural disaster (Round 1)	between		(0.05)	0.00	0.33	n	3629
	within		(0.07)	-0.33	0.67	T	3
	overall	0.01	(0.08)	0.00	1.00	N	10887
Natural disaster (Round 2)	between		(0.05)	0.00	0.33	n	3629
	within		(0.07)	-0.33	0.67	T	3
Natural disaster (Round 3)	overall	0.07	(0.26)	0.00	1.00	N	10887
	between		(0.14)	0.00	0.33	n	3629
	within		(0.22)	-0.26	0.74	T	3
	overall	0.35	(0.48)	0.00	1.00	N	10887
Education: < primary	between		(0.33)	0.00	1.00	n	3629
	within		(0.35)	-0.32	1.02	T	3
	overall	0.20	(0.40)	0.00	1.00	N	10887
Education: primary	between		(0.26)	0.00	1.00	n	3629
	within		(0.30)	-0.47	0.87	T	3
	overall	0.00	(0.04)	0.00	1.00	N	10887
Education: secondary	between		(0.02)	0.00	0.33	n	3629
	within		(0.03)	-0.33	0.67	T	3
	overall	0.45	(0.50)	0.00	1.00	N	10887
Education: post-secondary	between		(0.30)	0.00	1.00	n	3629
	within		(0.40)	-0.22	1.11	T	3

Table 4, Summary statistics, continued

Variable		Mean	Standard deviation	Minimum	Maximum		Observations
Housing quality	overall	0.94	(1.29)	0.00	20.36	N	10887
	between		(1.29)	0.00	20.36	n	3629
	within		(0.00)	0.94	0.94	T	3
Employed household head	overall	0.78	(0.41)	0.00	1.00	N	10887
	between		(0.20)	0.00	1.00	n	3629
	within		(0.36)	0.12	1.45	T	3
Sex household head	overall	0.34	(0.47)	0.00	1.00	N	10887
	between		(0.03)	0.00	0.67	n	3629
	within		(0.47)	-0.33	1.00	T	3
Savings(Rp)	overall	3.91E+07	(1.47 E+8)	0.00E+00	4.30E+09	N	10887
	between		(7.97 E+7)	0.00E+00	1.44E+09	n	3629
	within		(1.23 E+8)	-1.39E+09	2.90E+09	T	3
Homeowner	overall	0.89	(0.32)	0.00	1.00	N	10887
	between		(0.26)	0.00	1.00	n	3629
	within		(0.18)	0.22	1.55	T	3

Table 5 Predicted consumption regression results

Ln(Consumption)	Parameter		Standard Error
Disaster 92-97	0.14		(0.10)
Disaster 95-00	0.22		(0.15)
Disaster 02-07	-0.05		(0.05)
Savings	0.15	***	(0.03)
House quality	0.04		(0.04)
Animals	-0.06		(0.04)
Own house	0.07		(0.05)
Sex (Female)	-0.06		(0.14)
Age	0.01	**	(0.01)
Age^2	0.00	***	(0.00)
Ed, primary	0.07	**	(0.03)
Ed, secondary	0.15		(0.16)
Ed, post-secondary	0.04	*	(0.03)
Rural	0.04	**	(0.02)
Household size	0.06	***	(0.01)
Workers	-0.01		(0.01)
Pensioners	0.04		(0.05)
Constant	13.76	***	(0.03)
sigma_u	0.56		
sigma_e	0.48		
rho	0.57		
N	10887		
n	3269		
R ^{2}	0.7164		
F(4,3628)	336.33		
Prob > F	0.00		

Parameter estimates include household and year fixed effects; standard errors are robust standard errors.

Table 6 Fitted consumption predictions.

Consumption Predictions ($\bar{c}$)	Mean	Standard Deviation	Min	Max	Observations	
Overall	0.50	0.31	0.00	1.00	N	10887
between		0.01	0.44	0.60	n	3269
within		0.31	-0.09	1.06	T	3

Table 7 Correlates and breakdown of vulnerability in consumption

Average Value (in utils)	Vulnerability =	Poverty +	Aggregate Risk +	Idiosyncratic Risk +	Unexplained Risk
Variable	62.4***	24.81***	24.68***	0.2416***	12.95***
	[59.80, 64.90]	[22.30, 27.20]	[24.30, 25.90]	[0.22, 1.44]	[9.9, 14.8]
Disaster 92-97	0.47 **	0.39 **	0.06 ***	-0.02 *	0.03
	(0.22)	(0.18)	(0.02)	(0.01)	(0.05)
Disaster 95-00	-0.18 *	-0.13 *	-0.02 **	0.00	-0.04
	(0.10)	(0.08)	(0.01)	(0.02)	(0.07)
Disaster 02-07	-0.03	-0.01	0.00	-0.02 ***	0.00
	(0.03)	0.02	(0.00)	(4.64E-03)	(0.02)
Savings	-0.27 ***	-0.22 ***	-0.03 ***	0.00	-0.02
	(0.03)	0.02	(0.00)	(0.00)	(0.02)
Animals	-0.21 ***	-0.16 ***	-0.02 ***	0.01 ***	-0.02
	(0.06)	(0.05)	(0.01)	(3.58E-03)	(0.02)
Own House	-0.01	-0.01	0.00	-0.01	0.04
	(0.03)	(0.02)	(0.00)	(0.01)	(0.05)
Pensioners	-0.16 ***	-0.12 ***	-0.02 ***	0.00	-0.02
	(0.03)	(0.02)	(0.00)	(0.00)	(0.02)
Sex (Female)	-0.07 **	-0.06 **	-0.01 ***	-0.01 **	0.00
	(0.03)	(0.02)	3.13E-03	(0.00)	(0.02)
Age	0.01 ***	0.01 ***	6.85E-04 ***	0.00	0.00
	(0.00)	(2.62E-03)	(3.39E-04)	(0.00)	(0.00)
Age^2	0.00	-2.66E-05 *	-2.07E-06	5.41E-06 *	0.00
	(0.00)	(2.04E-05)	(2.64E-06)	(3.28E-06)	(0.00)
Ed, primary	-0.20 ***	-0.17 ***	-0.02 ***	0.00	-0.02
	0.02	0.02	(0.00)	(0.00)	(0.02)
Ed, secondary	-0.19	-0.20 *	-0.03 *	(dropped)	(dropped)
	(0.14)	(0.12)	(0.02)		
Ed, post-sec.	-0.23 ***	-0.20 ***	-0.03 ***	0.00	0.00
	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)
Rural	-0.08 ***	-0.06 ***	-0.01 ***	0.01 ***	0.00
	(0.02)	(0.01)	1.82E-03	(2.97E-03)	(0.01)
Household size	0.10 ***	0.09 ***	0.01 ***	0.00	0.01 **
	(3.12E-03)	(2.59E-03)	(0.00)	(0.00)	(2.29E-03)
Workers	0.01	0.01	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
R^2	0.29	0.28	0.29	0.24	0.17

N=10886; n=3629. Regressions include regional dummies. Numbers in parenthesis are bootstrapped standard errors and those in brackets are 90% confidence intervals. *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level, and * indicates significance at the 0.10 level.
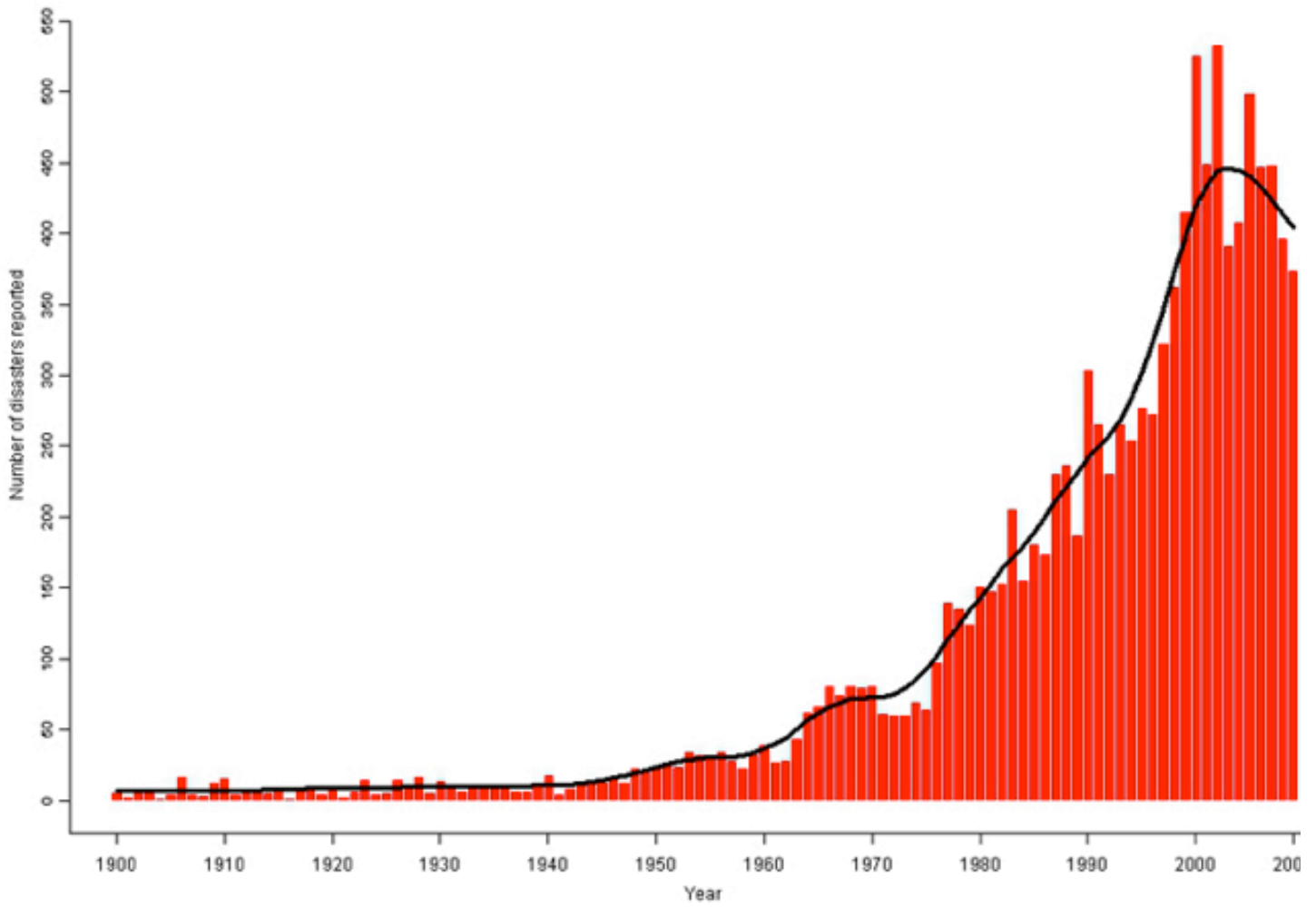
Figure 1. Number of annual natural disasters reported (source: EM-DAT)

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