Can extreme rainfall trigger democratic change?
The role of flood-induced corruption

Abstract

Using a new dataset of extreme rainfall covering 130 countries from 1979 to 2009, this paper investigates whether and how extreme rainfall-driven flooding affects democratic conditions. Our key finding is that extreme rainfall-induced flooding exerts two opposing effects on democracy. On one hand, flooding leads to corruption in the chains of emergency relief distribution and other post-disaster assistance, which in turn impels the citizenry to demand more democracy. On the other hand, flooding induces autocratic tendencies in incumbent regimes because efficient post-disaster management with no dissent, chaos or plunder might require government to undertake repressive actions. The net estimated effect is an improvement in democratic conditions.

Keywords: Extreme rainfall shocks, flood severity, corruption, democracy

JEL Classification: O0, P0

1. Introduction

A growing body of research highlights the crucial role played by environmental conditions in shaping the economic and political landscapes of nations (see Miguel, Satyanath and Sergenti 2004; Brückner and Ciccone 2011; Cole, Healy and Werker 2012; Nunn and Puga 2012; Dell, Jones and Olken 2014; Wood and Wright 2015). In this vein, rainfall shocks (i.e., droughts) have received considerable scholarly attention as a source of exogenous variation leading to significant changes in economic and political outcomes.

However, the extant literature tells us rather little about *extreme* rainfall, either as a relevant environmental concept or as an instigator of potentially dramatic changes in economic and democratic conditions. This study departs from the previous literature by focusing on the effects of extreme rainfall—the polar opposite of drought—on democracy. In particular, we examine a key mechanism through which extreme rainfall-driven flooding might affect democratic conditions: corruption. The primary reason to explore this transmission channel is that the potential consequences of extreme rainfall-driven flooding, such as widespread corruption in the distribution of relief actions following such flooding, can induce adverse public reactions against the incumbent government, which may lead to political regime changes.

Extreme rainfall merits scholarly attention for several reasons. First, some climatologists think that global warming is likely to increase the frequency and intensity of heavy rainfall incidents by the end of the 21st century. It has been predicted that a 1-in-20 years annual maximum daily precipitation is likely to become an event occurring 1-in-5 to 1-in-15 years by the end of the 21st century, particularly for high latitudes and tropical regions, and for the northern mid-latitude regions during winter (see Field 2012). Moreover, catastrophic flooding triggered by extreme rainfall not only claims thousands of lives but also destroys significant capital stocks and outputs. Over the 1979–2009 period, floods alone annually affected an average of over 122 million people globally (see CRED 2011).

Flooding victims may have strong reactions to ineffectiveness or corruption at the governmental level in emergency responses to flooding (see Leeson and Sobel 2011; Chang and Berdiev 2015). Natural disasters typically create windfalls in the form of aid and relief, which can boost fraudulent appropriation and theft (see Leeson and Sobel 2007; 2011; Yamamura 2014). As citizens' livelihoods already are in jeopardy owing to the disaster, such expropriation by public officials may lead citizens to revolt and remove the incumbent from power. This proposition is consistent with the so-called democratic efficiency theory and has received empirical support from Leeson and Sobel (2011) in the case of mayoral elections in New Orleans following 2005 Hurricane Katrina.[1] Akarca and Tansel (2016) provide more recent evidence, albeit for a different type of natural disaster, earthquakes. In examining the aftermath of the devastating 1999 earthquake in Turkey, Akarca and Tansel find that the Turkish electorate thereafter held accountable not only the dominant ruling party at the time of the earthquake but also other parties that were in power when the earthquake-vulnerable buildings were built.[2] The associated public outcry resulted in the 2002 electoral ouster of all three parties of the incumbent governing coalition. However, in spite of these case studies strongly linking disaster-driven corruption and electoral outcomes to the demand for public reform, the literature is ambiguous regarding the precise mechanisms through which such corruption ultimately affects democratic conditions.

[1] An earlier evidence on the public reaction against corruption is provided by Peters and Welch (1980), who show that corruption charges against candidates reduce the votes these candidates receive in US congressional elections by 6% to 11%. See also and Welch and Hibbing (1997).

[2] Escaleras, Anbarci and Register (2007) show that in countries with more corruption, earthquakes are more deadly.

An entirely different political impact of flooding on democracy is a direct effect in which floods prompt repression from the political regime owing to the chaos that often ensues following flooding events (Cole et al. 2012; Wood and Wright 2015). Such a direct effect may arise, independent of any other channel, when violence, dissent, and plunder occur in the post-flooding aftermath and leads to repressive responses by the incumbent regime (Davenport 2007, Wood and Wright 2015). Notably, the repressive reaction may be provoked because an authoritative form of governance might be understood as more efficient at relief distribution.[3,4]

Our empirical analysis documents that extreme rainfall-triggered flooding exerts two opposing effects on democratic conditions. On one hand, floods produce corruption in the distribution of relief, which, in turn, leads to more democracy. On the other hand, extreme rainfall-driven floods reinforce authoritarian tendencies in the incumbent political regime. Taken together, we find that the *net* effect of extreme rainfall-driven floods on political change is more democracy. Another key finding relates to the temporal effect of corruption on democracy: we show that flood-induced corruption in a given year has a significant positive impact on democracy over the next three years but that it disappears after the fourth year.

Next, we shed light on our key empirical result regarding the relationship between flood-induced corruption and more democracy with a simple dynamic game-theoretic model. Played between the government and the voters in three stages, the model illuminates the dynamics between the government's choices in tackling corruption during emergency response and voters'

[3] On a related, but nevertheless distinct topic, Sobel and Leeson (2006), Schultz and Libman (2015) and Escaleras and Register (2012) show how decentralized political institutions and local knowledge contribute to government effectiveness in responding to natural disasters.

[4] A well-known historical example the severe 1970 flooding in Eastern Pakistan, which acted as a catalyst for Bangladesh's Liberation War in 1971.

subsequent reaction to the government's choice in a forthcoming election. In the first stage, the government decides whether or not to provide costly action to prevent corruption in relief distribution following a disaster. After observing the government's choice, in the second stage, voters decide whether to keep the government in office or oust it from power. If the government remains in power, in the third stage, it decides whether to be autocratic or democratic, where being democratic is more costly than being autocratic. The equilibrium of this game is such that the government would choose to be democratic at the end because insurgency by the public when a government is *both* corrupt and autocratic following a disaster is very costly and difficult to neutralize.

The innovative feature of this model is its heuristic observation that a regime is unlikely to pursue a response trajectory that involves either double negatives (i.e., not preventing corruption and becoming autocratic) or a zero-negative (i.e., preventing corruption and becoming democratic) following a disaster. The more likely response involves only one negative in which the negative is associated with less cost to the government. Given our payoff structure, this response is "not prevent corruption but offer more democracy following the disaster." Several anecdotes around the world are consistent with similar games and outcomes, as explained in section 6.

Overall, this study traces two different components of political change following flooding events: a direct effect leading to an increased autocratic tendency, which we interpret to be due to the repressive stance of the incumbent to avert any plunder and/or to ensure efficient relief distribution, and an indirect effect resulting from increased corruption that eventually leads to more democracy as a result. Critically, our estimates show that the indirect effect (corruption-induced democracy) empirically dominates the direct effect. One explanation for this finding might be that citizens are willing to tolerate some repression in the aftermath of a flooding event because an authoritative government might be better at efficiently distributing relief and/or suppressing a violent minority that might endanger property rights in the midst of post-disaster chaotic environments. By contrast, fewer citizens tolerate corruption in the distribution of relief during periods of plight and grievance. The much larger proportion of citizens that is likely to become dissatisfied (and possibly insurgent) as a result of corruption in relief distribution might be driving the dominant effect of democratic improvement over repression.

2. Hypotheses on Extreme Rainfall, Flooding, and Democracy

2.1. Indirect Effect: Extreme Rainfall–Democracy Nexus through Corruption

The literature on the link between floods and corruption is rather scant. However, in a more general context, Leeson and Sobel (2008) note that the spatial map of natural disasters matches the geographical map of corruption in the US. In this body of research, at least three reasons can be identified for corruption following natural disasters. First, natural disasters generate resource windfalls in affected regions as a result of the influx of national emergency relief, and such resource windfalls might facilitate fraudulent misappropriation. Second, during post-disaster construction, the government itself may fraudulently award hefty contracts to lobbying firms in exchange for their support in future elections. Third, Hunt (2007) argues that the victims of catastrophic events are much more likely to bribe government officials than non-victims because victims are more likely to be desperate and vulnerable and to require public services immediately. Thus, the implication is that flooding can create a chaotic atmosphere that might in turn increase public officials' scope and likelihood of engaging in corruption.

However, the effects of flood-induced corruption on political conditions are ambiguous and may extend in both directions. On one hand, citizens may expect their flood-induced shortfall in income to be compensated—at least in part—by governmental relief. The shortfall or absence of such compensation due to corruption may lead to strong demands for public reform. In settings characterized by elections, such public outcry may also result in the weakening of the current government or even its ouster from power. Flood-induced income shortfalls may even lead citizens to contest the incumbent government by demonstrating because lower incomes reduce the opportunity costs involved with such challenges. This argument is consistent with the political transitions theory developed by Acemoglu and Robinson (2001). All these results may ultimately incentivize the government to become more democratic to counter-balance the dissent. On the other hand, flood-induced corruption might deteriorate democratic conditions. For example, corruption might reduce citizens' trust in the incumbent, leading them to opt for military rule or to elect populist-but-heavy-handed rulers, such as the late Hugo Chávez in Venezuela (see Seligson 2006). In addition, autocratic leaders may use the appropriated disaster aid to support their own power base and to augment their authority (Bueno de Mesquita and Smith 2009). It is widely documented that the Sri Lankan government and the Tamil Tigers competed over humanitarian aid following the 2004 tsunami. The Sri Lankan military used the hefty aid to weaken the Tamil Tigers and to end the multi-decade insurgency in 2009 (Beardsley and McQuinn 2009; Wood and Wright 2015). This outcome paved the way for a heavy-handed populist regime in the country. Thus, it is not immediately obvious how flood-induced corruption affects democracy. These arguments lead to our first hypothesis:

Hypothesis 1: Extreme rainfall-driven floods are likely to increase the scope and likelihood of corruption. The manner in which the resulting corruption affects the political regime is ambiguous.

2.2 Direct Effect: Extreme Rainfall, Floods and Democracy

The second source of political change following extreme rainfall-driven flooding consists of direct effects, i.e., the effects on political regimes that are independent of any specific channel. Several studies have both argued and provided evidence for the proposition that governments are likely to engage in repressive behavior following natural disasters. Such repression may seem optimal for several reasons. For example, incumbents can implement rapid and efficient relief distribution more easily under an autocratic than under a democratic form of governance because they need not consult legislative, judicial, and other organs in executing their disaster agenda. Governmental repression may also be provoked by large-scale violence, dissent, and political unrest that challenges the incumbent government, the existing balance of power and regime stability in the country (Wood and Wright 2015). In addition, severe disasters may constrain the state's capacity to deliver essential services such as power, water, public transportation and public health, aggravating the cognitive shock that citizens have already experienced as a result of the catastrophe. Moreover, in countries with weak protection of property and human rights, plunder and even murder may follow in the wake of the natural disaster. Finally, the exogenous shock to the economic and political system may exacerbate already unequal resource distribution, deepen ethnic cleavages, escalate political tensions, and provide opportunities to question the legitimacy and power of the state (Davenport 2007; Wood and Wright 2015). All these factors may induce strong nondemocratic and authoritarian reactions by the political regime. These arguments lead to our second hypothesis:

Hypothesis 2: Extreme rainfall-driven floods can provoke autocratic tendencies in political regimes independent of any channel because of the repression induced by violence, dissent and plunder following the natural disaster.

3. Data and Measurement

Each year, approximately 96,000 cubic kilometers of precipitation fall on the land surface of Earth, of which approximately 60,000 cubic kilometers are absorbed by human structures or infiltrated into the land, and the remaining 36,000 run off into oceans (see Huffman 2013).[5]

Rainfall is classified as "heavy" if precipitation is falling at rates greater than 7.5 mm (0.30 in) per hour.[6] Falling from clouds that are typically 2–7 km above the Earth's surface, heavy rainfall droplets range up to approximately 3 mm (0.13 in) in diameter, with a rate of fall of up to 7.6 m (25 ft) per second, depending on the size of the droplets. Raindrops typically range in number from 100–1,000 per cubic meter (3–30 per cubic foot). In general, a "heavy" raindrop may fall to Earth at a speed of up to 32 km (20 mi) per hour.

When the duration and intensity of the rainfall exceed the soil's ability to absorb the rain, excess water begins to run off. The average depth of runoff around the globe is approximately 27 cm, but there is considerable variation from this average, depending on the location. Annual runoff

[5] Each year, approximately 320,000 cubic kilometers of water evaporates from the oceans and 60,000 cubic kilometers evaporates from lakes, lagoons and streams. Of the total of 380,000 cubic kilometers of evaporation, approximately 284,000 cubic kilometers falls back into the world's oceans as precipitation and 96,000 onto the land surface, creating the hydrological cycle.

[6] Cherrapunji in northeast India experiences the world's heaviest rainfall of up to approximately 10,922 mm (430 in) per year. In the U.S., the heaviest rainfall amounts—up to 1778 mm (70 in)—are experienced in the southeast, followed by moderate annual accumulations, from 762–1270 mm (30–50 in), in the eastern U.S., and smaller accumulations, 381–1016 mm (15–40 in), in the central plains.

of over 100 cm occurs primarily in the tropics (i.e., in the tropical areas of Central America, the lower Amazon basin, equatorial West Africa, and Bangladesh and northeast India,) and in coastal alpine settings (i.e., in coastal Alaska and British Columbia, Norway, Chile and Argentina, Tasmania, and New Zealand). Each of these belts of exceptionally heavy runoff is surrounded by areas that receive approximately 50–100 cm of runoff annually. The areas producing less than 10 cm of runoff per year are extensive. The largest such contiguous area covers the north of Africa, the Arabian Peninsula, Iran, Afghanistan, Pakistan, and much of interior Asia. The interior of North America west of the 100th meridian and the Atacama and Patagonia in South America also produce little runoff.

In many cases, extreme rain-driven runoff is sufficient to swamp cities with weak infrastructure. For example, in July 2005, when Mumbai (India) received 94 cm of rain in one 24-hour span, flash flooding was triggered and claimed approximately 1,200 lives. As a result, over 20 million people were affected in Gujarat, Madhya Pradesh, Maharashtra, Goa, Orissa, Karnataka, Himachal Pradesh, Jammu and Kashmir (CRED 2011).

3.1. Data on Extreme Rainfall

Variations in extreme rainfall (i.e., variations in the higher end of the distribution of the rainfall volumes) constitute an exogenous source of change in terms of flooding severity.[7] We use NASA's GPCP database of monthly rainfall estimates for 130 countries over the 1979–2009 period to trace extreme rainfall occurrence. The GPCP database is the only database of its type that relies on both rain gauge and satellite data, as adjusted for systematic errors in rain gauge measurements.[8]

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[7] The contemporary hydrology literature demonstrates the relationship between runoff and flood severity. See Sui and Koehler (2001) and Cunderlik and Burn (2002).

[8] The correlation between our measure and alternative data sources such as the National Center for Environment Prediction and the UN Food and Agricultural Organization agro-climatic database is over 0.8.

3.2. Measuring Extreme Rainfall

Our extreme rainfall measure aims at capturing rainfall variations at the higher end of the rainfall volume distribution. The measure is based on monthly rainfall estimates over the 1979–2009 period observed at a 2.5°×2.5° latitude-longitude interval across 2,321 nodes in 130 countries (see Appendix A1 for a list of total number of nodes in each country).[9]

Given the monthly total rainfall volumes for each node, we first estimate the 90th percentile of monthly total rainfall during the 1979–2009 period for that node.[10] This estimate produces the threshold to identify the cut-off point for the monthly extreme rainfall that has occurred over the last 30 years. If the actual total rainfall in one month exceeds this threshold level, it is considered extreme rainfall at the nodal level. Finally, we sum all the extreme rainfall estimates in a given year for all the nodes within a country's boundary. Thus, the yearly extreme rainfall is calculated as follows: $R_{i,t}^{extreme} = \sum_{p=1}^{P} \sum_{m=1}^{12p} \left(R_{i,p,m,t}^{total} - R_{i,p,t}^{total\ at\ 90th\ percentile}\right)$, where R stands for rainfall, i represents the country, p indicates spatial nodes, m represents the month, and t denotes the year. In other words, our extreme rainfall metric takes the positive difference between the actual volume of total monthly rainfall in a given year and the 90th percentile of the average monthly total rainfall observed in the past 30 years for each nodal point on Earth. If the difference is negative, we set that value equal to zero, indicating the absence of extreme rainfall.

Our measure of extreme rainfall is likely to measure weather shocks. First, it captures extreme rainfall even when it occurs in an area in which rainfall is rare in retrospect.[11] Thus, Figure

[9] Adopting the standard deviation of monthly total rainfall in a given year for each 2.5° node to measure extreme rainfall yields qualitatively similar findings.
[10] Our results remain qualitatively similar using the 95th, 85th, 80th, and 75th percentile thresholds.
[11] For example, Makkah Province in Saudi Arabia faces severe seasonal flash floods notwithstanding that it is situated in an arid area characterized by high temperatures and low rainfall.

1 shows that country A has seven nodal points (i.e., A1–A7) and four high rainfall-prone zones (i.e., A3–A6) throughout the year, whereas country B has eight nodal points (i.e., B1–B8) and none that have experienced high levels of rainfall historically. Thus, it might be tempting to conclude that country A would be more extreme rainfall-prone than country B. However, the extreme rainfall threshold in our measure is much higher for rainfall-prone zones than the threshold level for rare-rainfall zones.[12] Second, our model traces out extreme rainfall on a monthly basis, accounting for seasonal variation at each node. Third, the 90th percentile threshold is applied to monthly average rainfall over the last 30 years, which captures the climatic conditions and leaves only the extreme weather shocks to examine.

3.3. Data on Flood Severity

We use the EM-DAT dataset of flood incidents (see, for instance, Kahn 2005; Keefer, Neumayer and Plümper 2011). The EM-DAT dataset is updated when a flood incident satisfies any of the following four criteria: (1) 10 or more people are reported killed; (2) 100 or more people are reported affected; (3) there is a call for international assistance; or (4) there is a declaration of a state of emergency. EM-DAT provides data on the total number of people who have died, are injured, made homeless or are otherwise affected. To measure flood severity, we add up the numbers of injured, homeless, and affected people. In the event that flooding occurs more than once in a given year, the annual total of the number of affected is used (see Keefer, Neumayer and Plümper 2011).

We are aware that extreme rainfall is generally a localized event, although its resultant outcomes—e.g., flooding—may not be always localized. However, the extent of flooding is

[12] The exclusion of smaller countries, such as country C in Figure 3, is unlikely to affect our results, as we employ a large panel of 130 countries and capture extreme rainfall variations on a small-scale interval, i.e., 2.5°×2.5°.

primarily a result of extreme rainfall in river basins that may be far upstream. Provided that the river basins are generally not small—as none in Asia and Africa are, in particular—we identify extreme rainfall at 2.5°×2.5° interval and then add up all such localized extreme rainfalls that occurred in a given year at the country level. Then, we sum all flood intensities—e.g., the number of people affected by flooding—within a country for the same year. This approach relates both localized flashfloods (i.e., floods resulting from extreme rainfall in the same locality) and riverine flooding (i.e., floods caused by extreme rainfall in a different locality) with our measure of extreme rainfall at the country level.

We measure democracy with the *Polity2* measure from the Polity IV project (Marshall and Jaggers 2005). Table 1 presents the descriptive statistics for the key variables used in this paper. The definitions and sources of all the variables are provided in Appendices A2 and A3.

4. Empirical Analysis

4.1 Single-Equation Estimation

We begin with a standard single-equation specification in which we model the effects of extreme rainfall intensity on the *Polity2* measure of democracy:

$$Polity2_{i,t} = \alpha_0 + \alpha_1 logExtremeRain_{i,t} + v_{i,t}$$

where i stands for country and t for time, $(logExtremeRain)$ is the log of extreme rainfall measure and *Polity2* is the democracy score. Country fixed effects, country-specific time trends, and common time effects are all controlled for in the model.

This model estimates the total net effect of extreme rainfall intensity on democracy. Column 1 in Table 2 reports no significant relationship in this vein. Several potential explanations follow. First, there simply may be no nexus between extreme rainfall and democracy. Second, the model might suffer as a result of omitted variables (e.g., extreme rainfall might have different effects in low- vs. high-income regimes). Third, extreme rainfall may affect democracy through mediating factors such as the number of people affected, or it may exhibit both *direct* effect and *indirect* effects. Further, the direct and indirect effects may differ in sign and make the total net effect ambiguous.

To investigate these effects, we first include income per capita and its quadratic in the model, which does not have any effect on the impact of extreme rainfall (columns 2 and 3). Next, we regress $Flood$ on democracy (column 4), and the OLS estimate is insignificant. To address possible endogeneity in this model, we next estimate the effect of flooding on democracy by using extreme rainfall as an instrumental variable in a limited information maximum likelihood estimation. The critical assumption here is that rainfall shocks affect democracy only by means of flooding. The top panel in columns 5 to 7 reports the second-stage estimates of the effects of the number of flood-affected people on democracy, whereas the bottom panel presents the first-stage effects of extreme rainfall on the number of people affected. Panel B in column 5 indicates that extreme rainfall is significantly linked to the number of people affected at the 5% level. However, such human casualties are not strong enough to affect democracy, see Panel A. Including income per capita and its quadratic in the model in columns 6 and 7, respectively, does not affect the results.

We next consider the corruption channel. However, estimating the indirect effects of flooding on democracy through corruption using a single equation model is implausibly complicated if not impossible. What is more feasible is to estimate the effects of flooding on corruption itself. Columns 8 to 10 show that extreme rainfall-driven flooding is insignificantly related to corruption in a single equation context.

4.2. The System of Equations Estimation

To track the relationship between extreme rainfall and democratic conditions via the corruption channel, we formulate a following type system of simultaneous equations:

(I) $Flood_{i,t} = \beta_0 + \beta_1 logExcessiveRain_{i,t} + \beta_2 \, logy_{i,t} + \beta_3 \, logy^2_{i,t} + \varepsilon_{i,t}$

(II) $Corrupt_{i,t} = \gamma_0 + \gamma_1 Flood_{i,t} + \gamma_2 logNY_{i,t} + \vartheta_{i,t}$

(III) $Polity2_{i,t} = \lambda_0 + \lambda_1 Corrupt_{i,t} + \lambda_2 Flood_{i,t} + \lambda_3 NP_{i,t} + \upsilon_{i,t}$

where *Corrupt* is corruption, $Flood$ is the total number of people affected by floods normalized by population in country i at time *t*, ($logExcessRain$) is the measure of extreme rainfall, $logy$ denotes real GDP per capita, and ($Polity2$) is the measure of democracy. Country-specific heterogeneity, country-specific time trends, and year-fixed effects are controlled for in all three equations. Notably, *Corrupt* measures the overall corruption in a country and not the component that is induced by flooding. However, with country-specific time trends controlled for in the model, γ_1 would pick up the component of corruption that diverges from the general corruption trend following flooding events.

Equation I of the system captures the effects of extreme rainfall on flood severity, $Flood$. Linear and quadratic forms of income ($logy$ and $logy^2$) are included in Equation I to control for the effects of the level of economic development or urbanization on flood intensity. The impact of floods largely depends on disaster preparedness levels and risk mitigation plans, and income can act as a reasonable proxy for both (see Noy 2009). ($logExcessRain$) is the distinct exogenous variable in Equation I that is required for system identification.

Equation II of the system captures the effects of $Flood$ on *Corrupt*. Hypothesis 1 posits that flooding is likely to increase the scope and likelihood of corruption. The average income of neighboring countries $(logNY)$ acts as the distinct exogenous variable required for system identification (see section 4.3 for the relevance and exogeneity of this variable).

In Equation III, *Corrupt* captures the indirect effects of extreme rainfall-driven floods on democracy. Hypothesis 1 posits that the impact of flood-induced corruption on democracy is ambiguous. This equation also estimates the impact of $Flood$ on $Polity2$. Here, $Flood$ represents the direct effects of the number of flood-affected citizens on democracy. In other words, it captures any effect of floods on democracy other than corruption. In our setting, this effect is likely to measure the repressive response of the incumbent regime following flood incidents. The average $Polity2$ score of neighboring countries (NP) is the distinct exogenous variable for system identification; for more on this variable, see below.

4.3 System Identification

The principal advantage of the system estimation is that it can capture both the direct and indirect effects of flooding on democracy. However, a typical criticism leveled against this method is that a misspecification can traverse through the equations, biasing the estimation. Our restrictive specification, which controls for country-specific heterogeneity, country-specific time trends, and year-specific effects, is expected to mitigate such drawbacks. Thus, we estimate our system using three-stage least squares (3SLS).

We next turn to identifying the system. Our key assumption in Equation I is that extreme rainfall affects corruption and *Polity2* only by means of flooding severity (i.e., the total number of people affected) and not through other mechanisms. One possibility violating this exclusion restriction is that extreme rainfall might not only strike the population but also destroy physical capital, which is likely to have an independent effect on output and $Polity2$. In an unreported exercise, we estimated the impact of extreme rainfall on gross capital formation but we did not observe a statistically significant relationship. Although this finding should not immediately discard the role of investment in the post-disaster phase, it is comforting for identification of our system that is based on annual panel data. Nonetheless, this restriction may be violated over the longer term.

A broad strand of the literature suggests that countries with open, large, and more developed neighboring economies experience faster growth than those with closed, smaller, and less-developed neighbors (See Ades and Chua 1997; Conley and Ligon 2002). Our assumption is that the average income of neighboring countries ($logNY$) can also co-vary with the domestic country's level of corruption. A richer neighbor might facilitate market competition and help new private and government agents enter into markets such that there is more competition among public and private agents. Such increased competition among rent-seeking bureaucrats can reduce corruption (see Ades and Di Tella, 1999; and Shleifer and Vishny, 1993). Richer and politically powerful neighbors might also push their neighbors to adopt more open and transparent policies. The fact that minimizing corruption is one of the accession conditions into the European Union for Central and Eastern European countries epitomizes this point.

Finally, the relevance of the weighted average $Polity2$ score of neighboring countries (NP) for $Polity2$ in Equation III is well established under the democratic domino theory.[13] For example, countries may compete for democratization to obtain international trade privileges and

[13] *See* Starr 1991; Starr and Lindborg 2003; Leeson and Dean 2009.

to attract foreign direct investment, or the diffusion effect may ignite democratization in neighboring countries as a result of social movements. In section 5.3, we undertake several robustness tests to examine the reliability of the neighbor-weighted variables.

Other threats to identification are likely to arise from permanent differences in country characteristics, common shocks across countries, and long-term trends in variables. We jointly control for country-specific fixed effects, country-specific time trends and common time effects in all the equations. Such a restrictive specification is likely to eliminate any spurious effects. Nonetheless, our empirical analysis assumes a careful approach by adding those characteristics to the system in stages to illuminate their role.

5. Results and Discussion

5.1. Extreme Rainfall-Driven Floods and Democracy

Model 3.1 presents the estimates for our system of simultaneous equations outlined in Equations I-III but with no fixed effects. Model 3.2 adds country fixed effects, whereas Model 3.3 is the most comprehensive specification that accounts also for country-specific time trends and common time effects. Standard errors, which are robust to any form of heteroscedasticity, are clustered at the country level.

Column 1 of Model 3.1 indicates that there is no statistically significant link between extreme rainfall and flood severity, which may result because countries with heterogeneous extreme rainfall intensities are likely to be better prepared for flooding, such as by having previously built structures (e.g., dams, water gates and barriers) that regulate water levels. Failing to control for these differences would lead the effects of extreme rainfall on flood severity to be biased downward, and as in our case, to possibly switch signs.

Not surprisingly, accounting for permanent country characteristics in Model 3.2 has a dramatic impact on the effects of extreme rainfall in Equation I, leading its sign not only to switch to positive but also to become statistically significant at the 5% level. In particular, column 4 indicates that a 10% increase in the volume of extreme rainfall increases the number of affected persons by one person per 100 people. Equation II in Model 3.2 indicates that rainfall-driven floods have significant effects on democracy (column 5). One in every 100 people affected by floods increases the PRS measure of corruption by 0.185 points on a scale of 0 to 6 (where higher scores denote more corruption).[14] Moreover, Equation III estimates that increased corruption is associated with a higher $Polity2$ score of 0.56 points (0.185 × 3.030) on a scale of [–10, 10], see column 6. This *indirect* effect of rainfall-driven floods on democracy is significant at the 1% level.

With regard to the *direct* effects of rainfall-driven floods on democracy, our estimates in Equation III of Model 3.2 indicate that flood severity had no impact on the *Polity2* score (column 6). However, this result must be interpreted with caution because it does not account for year fixed effects and country-specific time trends.

In this manner, we arrive at our preferred specification, which is provided in Model 3.3. After entirely isolating permanent country characteristics, common time effects, and country-specific time trends, we believe that any remaining variation in Model 3.3 is reasonably exogenous to outcome variables. Specifically, Model 3.3 indicates that excessive rainfall has a significant impact on flood severity (Equation I, column 7), which, in turn, has two significant and opposite effects on the *Polity2* measure of democracy. The *indirect* effect suggests that one in every 100

[14] Our sample indicates that 25 percent of flooding events around the world during the 1979–2009 period affected at least one percent of the country's population or more.

people affected by floods increases the PRS measure of corruption by 0.175 points on a scale of 0 to 6, which is significant at the 5% level (Equation II, column 8). This estimate supports the first component of Hypothesis 1 on the increased likelihood of corruption following floods. We also estimate that increased corruption is associated with a higher $Polity2$ score of 0.86 points (0.175 × 4.891) on a scale of [–10, 10], an effect that is significant at the 1% level (Equation III, column 9). This important evidence sheds significant light on the second component of Hypothesis 1 regarding what was *a priori* an ambiguous relationship between flood-induced corruption and democracy.

On the other hand, rainfall-driven floods have a *direct* and negative effect on democracy. Our estimates of Equation III in column 9 indicate that one in every 100 people affected by floods is associated with a $Polity2$ score that is 0.65 points lower, an effect that is significant at the 10% level. This evidence is consistent with the 'repression effect,' whereby the chaos stemming from violence, dissent, misappropriation and plunder following a natural disaster induces the political regime to resort to a nondemocratic response. This finding is consistent with Hypothesis 2 set forth above. In sum, the net effect of rainfall-driven floods in the presence of corruption is that one in every 100 people affected by floods in a given year leads to an improvement of 0.21 points (i.e., 0.86–0.65) in the *Polity2* measure of democracy. Given that the indirect effects are statistically superior, it seems safe to conclude that there is a net positive change in *Polity2* scores following extreme rainfall-driven floods.

5.2. Temporal Effects of Extreme Rainfall-Driven Floods on Democracy

Our estimates in Model 3.3 capture the contemporaneous response of democracy to extreme rainfall-driven floods. However, there might be lagged relationships with respect to both the direct and indirect effects. For example, citizens may not have an immediate option with regard to overthrowing the incumbent government (e.g., national elections may not be near). In addition, the government may impose repressive restrictions upon citizens for a longer time horizon to sustain itself in power. To determine whether there are in fact such temporal effects, we replace all variables in our preferred Model 3.3 with their associated lags of one-year (Model 4.1), two-years (Model 4.2), three-years (Model 4.3), and four-years (Model 4.4), except that we retain our main outcome variable *Polity2* at time *t*. Notably, in Models 4.1 to 4.4, our shifters (i.e., extreme rain, neighboring countries' average GDP and neighboring countries' average Polity2) turn out to be statistically significant at the 10% level, at least.

The lagged effects of the corruption channel are striking. The empirical estimates suggest that higher corruption due to extreme rainfall-driven floods is associated with more democracy in the next three consecutive years, at the 1% level of significance for the first two years and slightly beyond the 10% level of significance for the third year (Columns 3, 6 and 9). Importantly, the effect diminishes over time and disappears entirely after the fourth year (Column 12). The fading corruption effect on democracy implies that relief-related corruption is short-lived probably because the chance of expropriating relief is exhausted once the disaster-driven resource windfall is closed. This type of effect contrasts with the corruption effect that is longer lived, which is typically driven by rent-seeking activities within the state or government. A second reason for short-lived relief-related corruption might be that whereas such corruption is likely to involve a single party (e.g., government), rent-seeking activities typically involve multiple parties, including members of the public, which at bottom means greater enthusiasm for benefits. Overall, our result uncovers a new finding in this line of research that if flood relief-related expropriations are observed by citizens, they may demand polity reform over many years (rather than only contemporaneously), but this demand is relatively short-lived, as is the resource windfall and the consequent expropriation that ensues.[15]

In terms of lagged direct effects, these effects seem to prevail over the two years following the flooding (Columns 6 and 9) at the 10% level of significance. One explanation for this result is that the government may take flood-driven chaos as an opportunity to become non-democratic and to lengthen its incumbency; however, we do not read much into this evidence owing to its weaker statistical significance.

5.3. The Validity of the Exclusion Restrictions

As discussed in Section 4, the validity of the exclusion restriction is critical within our system context, i.e., extreme rainfall should have no systematic effects on country's level of corruption beyond the effect that it exerts on flood severity. Notwithstanding our very restrictive specification, one may argue that the exclusion restrictions might be violated if atmospheric conditions—such as trajectories of rainfall massed over a country—follow a similar trend in adjacent countries. In this case, a given rainfall incident may trigger similar mechanisms in adjacent countries, making it difficult to argue that the shock is unique to the country in question. A counter to this argument is that it is difficult for monthly rainfall incidents over a 30-year time period to form a consistent pattern of extreme rainfall catastrophes shared by neighboring countries to challenge the estimation. Nevertheless, we undertake a formal step to address this issue by controlling for neighbors' extreme rainfall (as weighted by neighbors' populations). If neighbors' extreme rainfall

[15] We would like to thank an anonymous reviewer for having revealed to us the lag effects in the timing of variables and their potential implications.

affects a country's income and democracy over and above its own incidents, then our exclusion restrictions may be violated. Nonetheless, Table 5 show neighbors' extreme rainfall to be insignificant in all our models.

Another concern is that the income of neighboring countries $(logNY)$ may influence $Polity2$ in Equation III through channels other than the country's own income. These mechanisms typically involve time-*variant* channels, and the main suspect in this case is trade and other bilateral links. We check whether trade with neighbors, which we measure as a spurt in trade with bordering countries, is associated with a similar spurt in the income and democracy of a country by including the share of neighbors in overall trade in Equations II and III, but any such association does not affect the results (unreported). Further, we control for whether a country is a member of a trading bloc, such as the European Union, Commonwealth of Independent States, North American Free Trade Agreement, Association of South East Asian Nations, or Gulf Cooperation Council. We find that such membership does not suggest a channel of concern for identification purposes (unreported).

Overall, these checks do not support the notion that neighbors affect a country through other channels in our context. Although all time-variant factors for both democracy and income cannot be conclusively excluded, our restrictive empirical design seems to eliminate significant indirect correlations that might otherwise jeopardize identification of the system.

6. Flood, Corruption and Democracy: A Simple Dynamic Game-Theoretic Model

What are the possible dynamics between flood-induced corruption and democratic improvement? We provide insights into this question with a simple dynamic game-theoretic model. Although there may be other explanations for the corruption-democracy nexus arising after floods, this model provides a novel insight into the link between governmental choice and citizens' reactions following a natural disaster.

The game is played by a government and voters following a natural disaster in three stages. See Figure 2. We use the following notation: $y =$ per capita income; $r =$ per capita cost of rain damage; $\pi =$ the incumbent government's payoff from re-election; $relief =$ per capita relief and rehabilitation after rain damage; c_c = governmental cost of preventing corruption; c_d = governmental cost of maintaining democracy; c_i = governmental cost of neutralizing the violent reaction that results from corrupt relief disbursement; $dem =$ voter benefit from having democracy; and $aut =$ voter cost of enduring autocracy.

6.1. Basic Setup

In the first stage of the game, the government decides whether and what moves to make knowing the rain damage, r. If no action is undertaken to remedy the rain damage, each voter's payoff is $y - r$, where y is standard per capita income. In the aftermath of flooding, there are ex-ante disaster-preparedness aids and ex-post international relief and rehabilitation to be allocated to the citizens, denoted as *relief*. However, these aids are subject to possible expropriation by officials/bureaucrats. In light of such corruption, *relief* will be ineffective. However, if the government intends to prevent corruption, it must incur a cost, c_c, to prevent *relief* from being misappropriated. The government will choose between allowing corruption versus preventing corruption depending on (1) the corruption-prevention cost, c_c,; (2) possible reactions of the voters in stage two regarding whether or not to re-elect the incumbent government after observing the government's actions with respect to corruption during the first stage; and (3) the government's further move in the third and final stage regarding its choice between authoritarianism vs.

democracy, i.e., if it is re-elected during the second stage. Therefore, both government and voter decisions and actions at each stage are common knowledge.

During the second stage, voters will decide whether to keep the current government in power or to vote it out in favor of a new government. The incumbent government will derive a payoff from staying in power if re-elected, denoted by π, and zero payoff from being voted-out. We assume that a new and unknown government can only provide voters with a base level of expected utility, *0*, beyond their status-quo payoffs. The voters' decision in stage two will depend on (i) whether the government has allowed corruption or not at stage one (i.e., whether *relief* was misappropriated or channeled to the voters) and (ii) the incumbent government's best interest at stage three in terms of choosing democracy vs. authoritarianism, if it is re-elected.

The incumbent government will make no further decisions if voted out at stage two. It will reach stage three only if it is re-elected, in which case it will incur a cost, c_d, if it chooses to maintain democracy because democratic decision making and implementing democratically made decisions is costly compared to the arbitrary decision making and implementation that characterizes autocracy. Voters obtain a positive payoff of *dem* if the government remains democratic, and a negative payoff of *aut* if it becomes autocratic. Further, if the incumbent government's authoritarianism allows corruption, the public will show its discontent through disobedience, which will be costly for the government to neutralize. To quell such insubordination, the government will face a cost of c_i. We assume that c_i is higher than both c_d and c_c, but we make no assumption as to whether c_d or c_c is larger.

6.2. Analysis

The analysis of such a dynamic game is conducted through "backward induction," which begins with the decision of the government at stage three. For simplicity, the game can analytically consist of two subgames, the *left-hand (LH) subgame* comprising all decision nodes following the government's choice of "corruption" and the *right-hand (RH) subgame* comprising all decision nodes after the government's choice of "no corruption" at stage one.

a. Stage Three

At this stage, the government will select as follows between the actions "democracy" and "autocracy":

- "Democracy" at its LH decision node since the payoff for "democracy" exceeds that of "autocracy," i.e., $\pi - c_d > \pi - c_i$ and
- "Autocracy" at its RH decision node since the payoff for "autocracy" exceeds that of "democracy," i.e., $\pi - c_c > \pi - c_c - c_d$.

b. Stage Two

Fully predicting the above-mentioned decisions of the government at stage three, in the LH subgame, voters will compare the payoff $y - r$ from "voting the government out" to the payoff $y - r + dem$ from "re-electing" it. In the RH subgame, voters will compare the payoff $y - r + relief$ from "voting out" the government to the payoff $y - r + relief - aut$ from "re-electing" it. Thus, given the government's choices of "democracy" at its LH decision node and "autocracy" at its RH decision node at stage three, at stage two, the voters will select as follows:

- To "re-elect" at its LH decision node since the payoff for "re-elect" exceeds that of "vote out," i.e., $y - r + dem > y - r$

- To "vote out" at its RH decision node since the payoff for "vote out" exceeds that of "re-elect," i.e., $y - r + relief > y - r + relief - aut$

c. *Stage One*

At this stage, the government will decide whether (or not) to prevent corruption, given that two choices will lie ahead: pick the LH subgame (i.e., allow corruption), for which the payoff will be $\pi - c_d$, or pick the RH subgame (i.e., prevent corruption), for which the payoff will be $0 - c_c$. Thus, given the *LH subgame*'s outcome, i.e., given voters' choice to "re-elect" at its LH decision node of stage two and the government's own choice of "democracy" at its LH decision node at stage three, and given the *RH subgame*'s outcome, i.e., given the voters' choice to "vote out" at its RH decision node of stage two and the government's own choice of "autocracy" at its RH decision at stage three,

at stage one, between the actions "corruption" vs. "no corruption," the government will select

- "Corruption" since the payoff for "corruption" exceeds that of "no corruption," i.e., $\pi - c_d > 0 - c_c$.

To summarize the equilibrium, the government allows corruption after the flood; the voters re-elect the incumbent government, predicting that it will choose to rule democratically after re-election; and the re-elected incumbent government will indeed be democratic.[16]

Several anecdotes around the world are consistent with this game, although political players might have followed different branches of the game tree. In reality, governments or citizens

[16] The off-equilibrium prediction of the model is that rampant corruption in the flood year is followed by less democracy in the subsequent year, but then the regime faces an insurgency. The model also implies that preventing corruption after flooding events can go hand in hand with autocracy off-the-equilbrium.

may not have perfect and/or complete information—which is different than in our model—and they may thus miscalculate. However, two cases are highly informative to put the game in perspective: Turkey in the wake of the 1999 earthquake and Brazil after enacting its anti-corruption program in 2003. The Turkish case is characterized by the left-most branch of game tree in which the three-party coalition government chose the corruption option in the aftermath the 1999 earthquake and was in turn voted out. The government had proven ineffective not only at preventing the misappropriated of disaster aid but also at chasing those who built the vulnerable structures.[17] The electorate voted out all three parties from parliament in 2002. Notably, the new government introduced revolutionary building and insurance codes and (importantly) offered more democracy within a few years after being elected. In the Brazilian case, the government promulgated an autonomous anti-corruption program in 2003 in an attempt to increase political transparency and to improve the disbursement of public transfers. Brollo (2012) shows that the program, which was set up to randomly audit local governments in terms of their public expenditures and lowers federal infrastructure allocations if corrupt activity is found, reduces the probability that corrupt local politicians will be re-elected. This achievement of decimating local-level corruption enabled the federal government to remain authoritarian, a prediction that is consistent with the right-most off-equilibrium branch of our game tree.

7. Conclusions

It has been predicted that the frequency and intensity of heavy rainfall incidents will increase by the end of the 21st century in several regions around the globe. A 1-in-20 year annual maximum

[17] Of more than 2,100 court cases opened to investigate the death of 17,280 people, the judiciary was able to punish only one contractor, Veli Göçer, who was sentenced to 7.5 years (for a total of 195 deaths in the sites he built) and became a public name. Hundreds of other contractors escaped punishment.

daily precipitation amount is likely to become a 1-in-5 to a 1-in-15 year event, particularly for high latitudes and tropical regions in the northern mid-latitudes during winter. Thus, extreme rainfall-driven flooding events, which are already formidable threats for both developing and developed countries, are likely to further challenge incumbent regimes by driving certain demands on the part of the citizenry if their governing structures include weak disaster management institutions.

Using a new measure of extreme rainfall covering a sample of 130 countries over the 1979–2009 period, our analysis strongly indicates that extreme rainfall-driven flood incidents result in two significant but opposing effects on democracy through the corruption channel. On one hand, extreme rainfall-driven floods increase corruption in the post-disaster emergency response and recovery efforts, which, in turn, leads people to demand more democracy. On the other hand, the extreme rainfall-driven flood incidents are associated with a 'repression' effect, which is likely to be induced by the chaos in the aftermath of the disaster, forcing government to resort to non-democratic behavior. Taken together, our key result is that the net effect of rainfall-driven floods is more democracy through the corruption mechanism. Moreover, we show that flood-induced corruption in a given year has significant effects on democracy for the next three years but that the effect dies out after the fourth year.

Next, we unpack the indirect effect, i.e., the relationship between flood-induced corruption and improvements in democracy by means of a game theoretic model. The game is played between the government and voters in three stages following a natural disaster, and the model sheds light on the dynamics related to the government's choice of whether to tackle corruption during the distribution of relief and emergency response and the voters' subsequent reaction to the government's choice. The model equilibrium suggests that it is costly for the government both to prevent corrupt conduct in the distribution of relief and to maintain democracy following the disaster. However, it is even costlier to allow corruption during the relief phase as well as to become autocratic following the disaster, given the insurgency threat that this doubly opportunistic stance would induce from the public. The model's equilibrium predicts a second-best outcome for both the government and voters: the government allows corruption to occur in emergency relief and response but improves democratic conditions following its re-election. This prediction rests on a heuristic observation that a regime is unlikely to pursue a response trajectory that involves either a double-negative (i.e., not preventing corruption and becoming autocratic) or a zero-negative (i.e., preventing corruption and becoming democratic) following a disaster. The more likely response is that which involves only one negative in which the negative is associated with lower cost to the government.

Overall, this study traces two different components of political change that occur in the aftermath of flooding events: a direct effect leading to an increased autocratic tendency in the incumbent regime, which we interpret to be due to a repressive response by the government in disaster management and an indirect effect through increased corruption that results in more democracy following the government's re-election. Our finding that the repression-led autocratic tendency is empirically dominated by corruption-induced democratic improvement suggests that citizens may be willing to accept autocratic tendencies in the regime for purposes of efficient relief distribution and/or protection of property rights during a disaster but that a larger subset of the population would be dissatisfied (and possibly insurgent) if there is corruption during the distribution of relief. Governments can overcome this challenge by offering to be more democratic.

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Tables and Figures

Figure 1: Schematic of the Extreme Rainfall Calculation

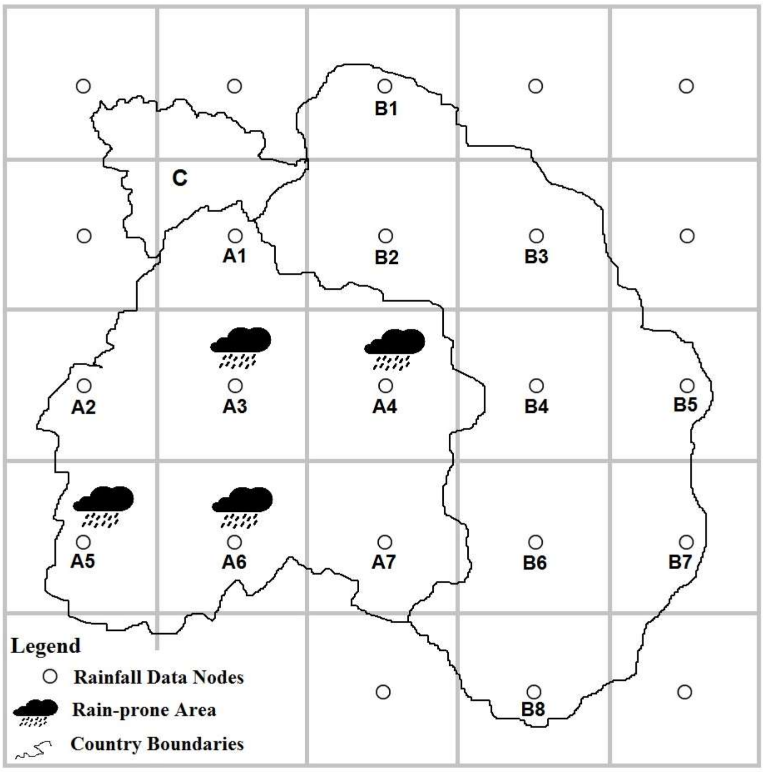

Table 1: Descriptive Statistics*

Variable	Mean	Standard deviation	Observations
Log extreme rainfall	4.746	2.159	4,031
Total affected by floods in every 100 people	0.621	4.581	6,773
Log neighboring nations' average GDP	26.172	1.763	4,538
Average of neighbors' Polity2	1.693	6.534	4,515
PRS corruption index	3.099	1.387	2,942
Polity2	1.170	7.346	4,354

Table 2: Extreme Rainfall, Corruption and Democracy: Single-Equation Estimation

Model	Polity2	Polity2	Polity2	Polity2	Polity2	Polity2	Polity2	PRS Corruption Index	PRS Corruption Index	PRS Corruption Index
	LS	LS	LS	LS	IV-LIML	IV-LIML	IV-LIML	LS	LS	IV-LIML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A:										
Log Extreme Rainfall	0.003	-0.0002	0.0003					0.006		
	(0.032)	(0.032)	(0.032)					(0.007)		
No. of Flood-Affected Persons in Every 100 People				0.008	0.016	-0.001	0.002		0.002	0.053
				(0.015)	(0.150)	(0.149)	(0.148)		(0.002)	(0.068)
Log Y		-0.272	1.815			-0.273	1.818			
		(0.877)	(4.349)			(0.872)	(4.339)			
Log Y^2			-0.140				-0.141			
			(0.285)				(0.285)			
Panel B:					***First Stage for No. of Flood-Affected Persons in Every 100 People***					
Log Extreme Rainfall					0.203	0.205	0.205			0.100
					(0.080)**	(0.080)**	(0.080)**			(0.062)
Log Y						-0.470	-1.838			
						(0.423)	(2.143)			
Log Y^2							0.092			
							(0.140)			
Kleiberg-Paap F-Statistic					6.49	6.55	6.52			2.66
Observations	3,315	3,272	3,272	3,315	3,315	3,272	3,272	2,268	2,268	2,268

Robust standard errors (in parentheses) are clustered at the country level. LIML: Fuller limited information maximum likelihood. Y: Real GDP Per Capita. All equations include country fixed effects, country time trends and common time effects. *significant at 10% level; **significant at 5% level; and ***significant at 1% level.

Table 3: Extreme Rainfall, Corruption and Democracy: System Estimation

VARIABLES	(1) No. of Flood-Affected in Every 100 People	(2) PRS Corruption Index	(3) Polity2	(4) No. of Flood-Affected Persons in Every 100 People	(5) PRS Corruption Index	(6) Polity2	(7) No. of Flood-Affected Persons in Every 100 People	(8) PRS Corruption Index	(9) Polity2
	Model 3.1			Model 3.2			Model 3.3		
Log Extreme Rainfall	-0.022			0.098			0.065		
	(0.015)			(0.040)**			(0.038)*		
Log Y	2.222			-6.523			-5.575		
	(0.261)***			(1.441)***			(2.241)**		
Log Y^2	-0.159			0.420			0.281		
	(0.016)***			(0.089)***			(0.154)*		
No. of Flood-Affected Persons in Every 100 People		1.189	3.236		0.185	-0.369		0.175	-0.649
		(0.073)***	(0.251)***		(0.097)*	(0.430)		(0.089)**	(0.392)*
Log Neighbors' Average GDP		-0.067			0.799			-0.206	
		(0.024)***			(0.050)***			(0.083)**	
Neighbors' Average Polity2			0.440			0.448			0.129
			(0.025)***			(0.030)***			(0.032)***
PRS Corruption Index			-4.982			3.030			4.891
			(0.266)***			(0.325)***			(0.875)***
Country Fixed Effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	No	No	No	No	No	No	Yes	Yes	Yes
Common Time Effects	No	No	No	No	No	No	Yes	Yes	Yes
Observations	2,268	2,268	2,268	2,268	2,268	2,268	2,268	2,268	2,268

See the notes to Table 2.

Table 4: Temporal Effects of Extreme Rainfall-Driven Floods, Corruption and Democracy

VARIABLES	(1) No. of Flood-Affected Persons in Every 100 People, t-1	(2) PRS Corruption Index, t-1	(3) Polity2, t	(4) No. of Flood-Affected Persons in Every 100 People, t-2	(5) PRS Corruption Index, t-2	(6) Polity2, t	(7) No. of Flood-Affected Persons in Every 100 People, t-3	(8) PRS Corruption Index, t-3	(9) Polity2, t	(10) No. of Flood-Affected Persons in Every 100 People, t-4	(11) PRS Corruption Index, t-4	(12) Polity2, t
	Model 4.1: All explanatory variables are lagged by one year			Model 4.2: All explanatory variables are lagged by two years			Model 4.3: All explanatory variables are lagged by three years			Model 4.4: All explanatory variables are lagged by four years		
Log Extreme Rainfall	0.0664			0.0665			0.0654			0.0644		
	(0.0379)*			(0.0377)*			(0.0375)*			(0.0396)		
Log Y	-5.794			-6.402			-6.318			-6.458		
	(2.263)**			(2.290)***			(2.263)***			(2.326)***		
Log Y^2	0.301			0.344			0.335			0.338		
	(0.156)*			(0.157)**			(0.154)**			(0.159)**		
No. of Flood-Affected Persons		0.178	-0.440		0.169	-0.643		0.161	-0.584		0.173	-0.403
in Every 100 People		(0.0884)**	(0.342)		(0.0868)*	(0.337)*		(0.0866)*	(0.322)*		(0.0896)*	(0.289)
Log Neighbors' Average GDP		-0.232			-0.200			-0.176			-0.179	
		(0.0896)***			(0.0929)**			(0.0960)*			(0.0997)*	
Neighbors' Average Polity2			0.107			0.0954			0.0828			0.0568
			(0.0312)***			(0.0305)***			(0.0297)***			(0.0284)**
PRS Corruption Index			3.254			2.884			1.277			-0.00632
			(0.834)***			(0.818)***			(0.821)			(0.766)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,267	2,267	2,267	2,266	2,266	2,266	2,265	2,265	2,265	2,157	2,157	2,157

See the notes to Table 2.

Table 5. Neighbors' Extreme Rainfall: Checking the Exclusion Restriction

VARIABLES	(1) No. of Flood-Affected Persons in Every 100 People	(2) PRS Corruption Index	(3) Polity2	(4) No. of Flood-Affected Persons in Every 100 People	(5) PRS Corruption Index	(6) Polity2	(7) No. of Flood-Affected Persons in Every 100 People	(8) PRS Corruption Index	(9) Polity2
	4.1: Sample with available neighbors' extreme rainfall data			4.2: Neighbours' extreme rainfall weighted by population			4.3: Neighbours' extreme rainfall weighted by GDP		
Log Extreme Rainfall	0.110			0.090			0.093		
	(0.039)***			(0.042)**			(0.041)**		
Log Y	-6.250			-6.053			-6.220		
	(2.457)**			(2.286)***			(2.267)***		
Log Y^2	0.356			0.332			0.344		
	(0.170)**			(0.157)**			(0.156)**		
No. of Flood-Affected Persons in Every 100 people		0.129	-0.631		0.165	-0.447		0.165	-0.541
		(0.066)**	(0.344)*		(0.083)**	(0.392)		(0.082)**	(0.394)
Log Neighbors' Average GDP		-0.149			-0.155			-0.133	
		(0.078)*			(0.080)*			(0.079)*	
PRS Corruption Index			5.722			4.966			5.081
			(0.850)***			(0.879)***			(0.888)***
Neighbors' Average Polity2			0.191			0.190			0.188
			(0.036)***			(0.036)***			(0.035)***
Log Neighbors' Extreme Rainfall Weighted by Population				0.083	-1.021	-0.078			
				(0.080)	(2.023)	(0.106)			
Log Neighbors' Extreme Rainfall Weighted by GDP							0.072	-1.024	-0.015
							(0.073)	(2.021)	(0.098)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Common Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,973	1,973	1,973	1,973	1,973	1,973	1,973	1,973	1,973

See the notes to Table 2.

Figure 2: A Simple Theoretical Model