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

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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 indicates 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 et al. 2004; Brückner and Ciccone 2011; Cole et al. 2012; Nunn and Puga 2012; Dell et al. 2014; Wood

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and Wright 2016). 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 year annual maximum daily precipitation is likely to become an event occurring 1-in-5 to 1-in-15 year 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).

The direct impact of flooding on democracy arises owing to the repression by the political regime prompted by the chaos that often ensues following flooding events (Cole et al. 2012; Wood and Wright 2016). Such a direct effect may emerge, independent of any other channel, when violence, dissent, and plunder occur in the aftermath of flooding, leading to repressive responses by the incumbent regime (Davenport 2007; Wood and Wright 2016). Notably, the repressive reaction may be provoked because an authoritative form of governance might be understood as more efficient at relief distribution.[1,2]

An entirely different political impact of flooding on democracy is a channel effect where the flooding victims may have strong reactions to governmental ineffectiveness or corruption 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.[3] 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

[1] 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.

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

[3] 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 6–11%. See also Welch and Hibbing (1997).

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.[4] 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.

We commence the paper by addressing the equivocal relationship between flood-induced corruption and democratic change 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 responses and voters' 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 "do 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 Sect. 3.

Our following empirical investigation tests the direct repression effect and indirect effect through corruption of extreme rainfall-triggered flooding on democratic conditions using a new dataset of extreme rainfall covering 130 countries from 1979 to 2009. We find that, 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. It is conceivable that these effects take place in countries with somewhat authoritarian initial conditions. Critically, our estimates show that the indirect effect (corruption-induced democracy) dominates the direct effect empirically. Overall, the *net* effect of extreme rainfall-driven floods on political change is more democracy. One explanation for the dominating indirect effect might be that citizens are willing to tolerate some repression in the aftermath of a flooding event because an authoritarian government might be better at efficiently distributing relief and/or suppressing a violent minority that might endanger property rights in the midst of chaotic post-disaster environments. By contrast, fewer citizens tolerate corruption in the distribution of relief following disaster events. 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 the driving force in explaining the dominance of democratic improvement over repression. Another key finding in our empirical analysis relates to the temporal effect of corruption on democracy: we find that flood-induced corruption in a

[4] Escaleras et al. (2007) show that in countries with more corruption, earthquakes are more deadly.

given year has a significant positive impact on democracy over the next three years, but that it disappears after the fourth year.

Overall, this study traces two different components of political change following flooding events: a direct effect reinforcing autocratic tendencies, which we interpret as being explained by the incumbent government's repression to avert plunder and/or to ensure efficient relief distribution, and an indirect effect resulting from public responses to corruption that eventually leads to more democracy.

2 Direct effect: extreme rainfall, floods and democracy

The first source of political change following extreme rainfall-driven flooding consists of direct effects, i.e., the effects on governing regimes that are independent of any specific transmission 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 other branches in executing their disaster agendas. Governmental repression may also be provoked by large-scale violence, dissent and political unrest that challenges the incumbent regime or threatens the existing balance of power and stability in the country (Wood and Wright 2016). 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 already have experienced as a result of the catastrophe. Moreover, in countries with weak protections for 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 distributions, deepen ethnic cleavages, escalate political tensions, and provide opportunities to question the legitimacy and power of the state (Davenport 2007; Wood and Wright 2016). All of these factors may induce strong nondemocratic and authoritarian reactions by the political regime. These arguments lead to our first hypothesis:

Hypothesis 1 Extreme rainfall-driven floods can provoke autocratic tendencies in political regimes independent of any other channel owing to the repression induced by violence, dissent and plunder following the natural disaster.

3 Indirect effect: the corruption nexus

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 United States. 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 reconstruction, the government itself may fraudulently award hefty contracts to politically influential 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, vulnerable and in need of public services immediately. Thus, the implication is that flooding can create a chaotic atmosphere that might in turn increase public officials' discretion and likelihood of engaging in corruption.

However, the effects of flood-induced corruption on political conditions are ambiguous and may extend in two directions. On one hand, citizens may expect their flood-induced shortfall in income to be counterbalanced—at least in part—by governmental relief. The shortfall or absence of such aid because of public corruption may lead to strong demands for 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 protest against the incumbent government because lower incomes reduce the opportunity costs of such demonstrations. This argument is consistent with the political transitions theory developed by Acemoglu and Robinson (2001). Public protests ultimately may incentivize the government to become more democratic to undermine the dissent. On the other hand, flood-induced corruption might deteriorate democratic conditions. For example, corruption might reduce citizens' trust in the incumbent regime, 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 disaster aid to support their own power bases 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 resource windfall to weaken the Tamil Tigers and to end their multi-decade insurgency in 2009 (Beardsley and McQuinn 2009; Wood and Wright 2016). This outcome paved the way for a heavy-handed populist regime. Thus, it is not immediately obvious how flood-induced corruption affects democracy.

Taken together, while the extant scholarly work is relatively clear on role played by extreme rainfall-driven flooding on the scope of public sector corruption, the manner in which the resulting corruption affects the political regime is somewhat obscure. Thus, we next provide insights into the polity effect of flood-induced corruption by means of a game-theoretic model.

3.1 Flood, corruption and democracy: a simple dynamic game-theoretic model

What are the possible dynamics between flood-induced corruption and democratic improvement? Many explanations are possible for the corruption-democracy nexus arising after floods, but the core of the answer lies in the governmental choice and citizens' reactions following a natural disaster.

Our game is played by a government and voters following a natural disaster in three stages. See Fig. 1. We use the following notation: y = per capita income; r = per capita cost of rain damage; π = the incumbent government's payoff from reelection; *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.

3.1.1 *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

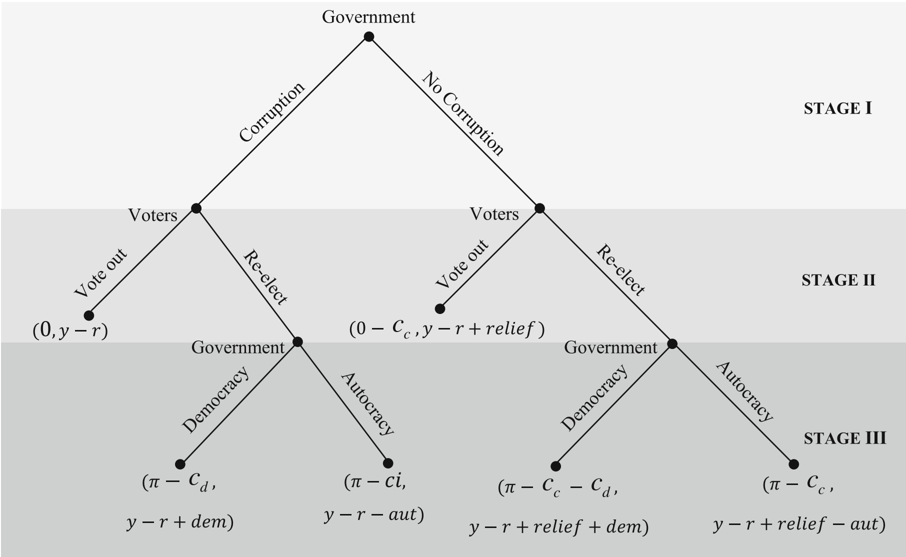

Fig. 1 A simple theoretical model

voter's payoff is $y - r$, where y is standard per capita income. In the aftermath of flooding, ex-ante disaster-preparedness aids and ex-post international relief and rehabilitation are 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 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 reelect 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 versus democracy, i.e., if it is reelected 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 reelected, denoted by π, and zero payoff from being voted out of office. We assume that a new and unknown government can provide voters only 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 affected voters) and (ii) the incumbent government's best interest at stage three in terms of choosing democracy or authoritarianism, if it is reelected.

The incumbent government will make no further decisions if voted out at stage two. It will reach stage three only if it is reelected, 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. Furthermore, 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.

3.1.2 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 consist analytically 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 "reelecting" 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 "reelecting" 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 "reelect" at its LH decision node since the payoff for "reelect" 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 "reelect," 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 "reelect" 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" versus "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 reelect the incumbent government, predicting that it will choose to rule democratically after reelection; and the reelected incumbent government will indeed be democratic.[5]

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 may not have perfect or complete information—which is different than in our model—and thus they may miscalculate. However, two cases are highly informative for putting 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 of the 1999 earthquake and was in turn voted out. The government had proven ineffective not only at preventing the misappropriation of disaster aid but also at chasing those who built the vulnerable structures.[6] 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 cut federal infrastructure allocations if corrupt activity is found, reduces the probability that corrupt local politicians will be reelected. This achievement of mitigating 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.

Thus, considering the discussion above as well as the equilibrium outcome of this game-theoretic model, our second hypothesis for empirical analysis is:

Hypothesis 2 Extreme rainfall-driven floods are likely to increase the scope and likelihood of public-sector corruption. Flood-induced corruption, in turn, leads to more democracy.

4 Data and measurement

Each year, approximately 96,000 km^3 of precipitation fall on the Earth's land surface, of which approximately 60,000 km^3 fall on buildings and homes or infiltrate the land, while the remaining 36,000 run off into oceans (see Huffman 2013).[7]

[5] 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.

[6] Of more than 2100 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.

[7] Each year, approximately 320,000 km^3 of water evaporates from the oceans and 60,000 km^3 evaporates from lakes, lagoons and streams. Of the total of 380,000 km^3 of evaporation, approximately 284,000 km^3 falls back into the world's oceans as precipitation and 96,000 onto the land surface, creating the hydrological cycle.

Rainfall is classified as "heavy" if precipitation is falling at rates greater than 7.5 mm (0.30 in.) per hour.[8] Descending from clouds that typically are 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 100–1000 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 it, excess water begins to run off. The average depth of runoff around the globe is approximately 27 cm, but varies considerably from this average, depending on the location. Annual runoff 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. Areas producing >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 experience 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-h span, flash flooding was triggered and claimed approximately 1200 lives. As a result, more than 20 million people were affected in Gujarat, Madhya Pradesh, Maharashtra, Goa, Orissa, Karnataka, Himachal Pradesh, Jammu and Kashmir (CRED 2011).

4.1 Data on extreme rainfall

Variations in extreme rainfall (i.e., variations at the upper end of the distribution of the rainfall volumes) constitute an exogenous source of change in terms of flooding severity.[9] We use NASA's Global Precipitation Climatology Project (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 catalog of its type that relies on both rain gauge and satellite data, as adjusted for systematic errors in rain gauge measurements.[10]

4.2 Measuring extreme rainfall

Our extreme rainfall measure aims at capturing rainfall variations at the upper 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

[8] Cherrapunji in northeast India experiences the world's heaviest rainfall of up to approximately 10,922 mm (430 in.) per year. In the United States, 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 United States, and smaller accumulations, 381–1016 mm (15–40 in.), in the central plains.

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

[10] 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 exceeds 0.8.

2321 nodes in 130 countries (see Appendix 1 for a list of total number of nodes in each country).[11]

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.[12] This estimate produces the threshold to identify the cut-off point for the monthly extreme rainfall observed over the past 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 nodes within a country's boundary. Thus, the yearly extreme rainfall is calculated as follows:

$$R_{i,t}^{extreme} = \sum_{p=1}^{P}\sum_{m=1}^{12}\left(R_{i,p,m,t}^{total} - R_{i,p,t}^{total\,at\,90th\,percentile}\right)$$

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 over 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.[13] Thus, Fig. 2 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.[14] 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.

4.3 Data on flood severity

We use the Emergency Database (EM-DAT) dataset of flood incidents (see, for instance, Kahn 2005; Keefer et al. 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) a call for international assistance is issued; or (4) a state of emergency is declared. 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

[11] 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.

[12] Our results remain qualitatively similar using the 95th, 85th, 80th and 75th percentile thresholds.

[13] 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.

[14] The exclusion of smaller countries, such as country C in Fig. 2, 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°.

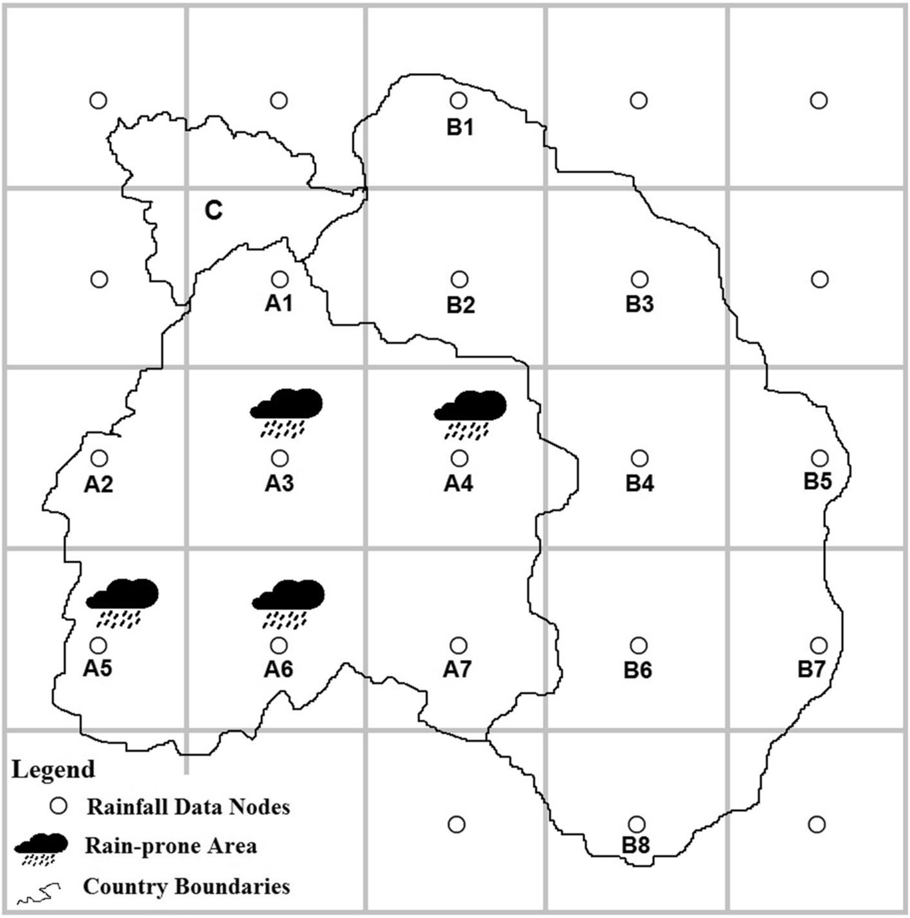

Fig. 2 Schematic of the extreme rainfall calculation

flooding occurs more than once in a given year, the annual total of the number of people affected is used (see Keefer et al. 2011).

We are aware that extreme rainfall generally is a localized event, although its resultant outcomes—e.g., flooding—may not always be localized. However, the extent of flooding primarily results from extreme rainfall in river basins that may be far upstream. Provided that the river basins generally are not small—as none in Asia and Africa are, in particular—we identify extreme rainfall at 2.5°× 2.5° intervals 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 combines 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) in our measure of extreme rainfall at the country level.

We measure democracy with the *Polity*2 measure from the Polity IV project (Marshall and Jaggers 2005). Table 1 presents the descriptive statistics for the key variables used in

Table 1 Descriptive statistics

Variable	Mean	SD	Observations
Log extreme rainfall	4.746	2.159	4031
Total affected by floods in every 100 people	0.621	4.581	6773
Log neighboring nations' average GDP	26.172	1.763	4538
Average of neighbors' Polity2	1.693	6.534	4515
PRS corruption index	3.099	1.387	2942
Polity2	1.170	7.346	4354

this paper. The definitions and sources of all the variables are provided in Appendices 2 and 3.

5 Empirical analysis

5.1 Single-equation estimation

We commence with a standard single-equation specification in which we model the effects of extreme rainfall intensity on the *Polity*2 measure of democracy:

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

where i stands for country and t for time, *log Extreme Rain* is the log of extreme rainfall measure and *Polity*2 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 from omitted variables (e.g., extreme rainfall might have different effects in low- versus 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 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; neither variable has any effect on the impact of extreme rainfall (columns 2 and 3). Next, we regress *Flood* on democracy (column 4), and the OLS coefficient estimate is insignificant. To address possible endogeneity in this model, we next explore 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.

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 number 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	3315	3272	3272	3315	3315	3272	3272	2268	2268	2268

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	Model 3.1			Model 3.2			Model 3.3		
	No. of flood-affected persons in every 100 people (1)	PRS corruption index (2)	Polity2 (3)	No. of flood-affected persons in every 100 people (4)	PRS corruption index (5)	Polity2 (6)	No. of flood-affected persons in every 100 people (7)	PRS corruption index (8)	Polity2 (9)
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	2268	2268	2268	2268	2268	2268	2268	2268	2268

Robust standard errors (in parentheses) are clustered at the country level. The estimation method is three-stage least squares

* Significant at 10% level; ** significant at 5% level; and *** significant at 1% level

Table 4 Temporal effects of extreme rainfall-driven floods, corruption and democracy

Variables	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		
	No. of flood-affected persons in every 100 people, t − 1	PRS corruption index, t − 1	Polity2, t	No. of flood-affected persons in every 100 people, t − 2	PRS corruption index, t − 2	Polity2, t	No. of flood-affected persons in every 100 people, t − 3	PRS corruption index, t − 3	Polity2, t	No. of flood-affected persons in every 100 people, t − 4	PRS corruption index, t − 4	Polity2, t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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 in every 100 people		0.178	−0.440		0.169	−0.643		0.161	−0.584		0.173	−0.403
		(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)

Table 4 continued

Variables	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		
	No. of flood-affected persons in every 100 people, t − 1	PRS corruption index, t − 1	Polity2, t	No. of flood-affected persons in every 100 people, t − 2	PRS corruption index, t − 2	Polity2, t	No. of flood-affected persons in every 100 people, t − 3	PRS corruption index, t − 3	Polity2, t	No. of flood-affected persons in every 100 people, t − 4	PRS corruption index, t − 4	Polity2, t
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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	2267	2267	2267	2266	2266	2266	2265	2265	2265	2157	2157	2157

See the notes to Table 3

We next consider the corruption channel. However, estimating the indirect effects of flooding on democracy (channeled 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.

5.2 The system of equations estimation

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

$$Flood_{i,t} = \beta_0 + \beta_1 logExtremeRain_{i,t} + \beta_2 logy_{i,t} + \beta_3 logy^2_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$Corrupt_{i,t} = \gamma_0 + \gamma_1 Flood_{i,t} + \gamma_2 logNY_{i,t} + \vartheta_{i,t} \tag{2}$$

$$Polity2_{i,t} = \lambda_0 + \lambda_1 Corrupt_{i,t} + \lambda_2 Flood_{i,t} + \lambda_3 NP_{i,t} + \upsilon_{i,t}, \tag{3}$$

where *Corrupt* is corruption, *Flood* is the total number of people affected by floods normalized by population in country *i* at time *t, logExtremeRain* is the measure of extreme rainfall, *logy* denotes real GDP per capita, and *Polity*2 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 entered into the model, γ_1 would pick up the component of corruption that diverges from the general corruption trend following flooding events.

Equation (1) 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 Eq. (1) 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 and risk mitigation plans, and income can act as a reasonable proxy for both (see Noy 2009). Finally, *logExcessRain* is the distinct exogenous variable in Eq. (1) that is required for system identification.

Equation (2) of the system captures the effects of *Flood* on *Corrupt*. Hypothesis 2 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 Sect. 5.3 for the relevance and exogeneity of this variable).

In Eq. (3), *Corrupt* captures the indirect effects of extreme rainfall-driven floods on democracy. Hypothesis 2 posits that the impact of flood-induced corruption on democracy is positive. This equation also estimates the impact of *Flood* on *Polity*2. 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. Hypothesis 1 states that the expected effect would be autocracy-inducing. The average *Polity*2 score of neighboring countries (*NP*) is the distinct exogenous variable for system identification; for more on this variable, see below.

5.3 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 crisscross 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 Eq. (1) is that extreme rainfall affects corruption and *Polity*2 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 *Polity*2. 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 rule out investment's role 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 foster openness and accountability, thereby promoting competitiveness in the home county's public and private sectors. More competition among rent-seeking bureaucrats can reduce corruption (see Ades and Di Tella 1999; Shleifer and Vishny 1993). Richer and politically powerful neighbors might also push their neighbors to adopt more 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 *Polity*2 score of neighboring countries (NP) for *Polity*2 in Eq. (3) is well established under the democratic domino theory.[15] For example, countries may compete for democratization to obtain international trade privileges and to attract foreign direct investment, or the diffusion effect may ignite democratization in neighboring countries as a result of social movements. In Sect. 6.3, 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 explanatory 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.

6 Results and discussion

6.1 Extreme rainfall-driven floods and democracy

In Table 3, Model 3.1 presents the estimates for our system of simultaneous equations outlined in Eqs. (1)–(3) 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-

[15] *See* Starr (1991), Starr and Lindborg (2003) and Leeson and Dean (2009).

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 no statistically significant link exists 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 infrastructure (e.g., dams, water gates and barriers) that regulate water levels. Failing to control for these differences would bias the effects of extreme rainfall on flood severity downward and, as in our case, cause them possibly to switch signs.

Not surprisingly, accounting for permanent country characteristics in Model 3.2 has a dramatic impact on the effects of extreme rainfall in Eq. (1), 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 victims by one person per 100 population. Equation (2) in Model 3.2 indicates that rainfall-driven floods have significant effects on corruption (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).[16] Moreover, Eq. (3) estimates that more corruption is associated with a *Polity*2 score of 0.56 points higher (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 Eq. (3) of Model 3.2 indicate that flood severity had no impact on the *Polity*2 score (column 6). However, that 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 reported 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 extreme rainfall has a significant impact on flood severity (Eq. 1, column 7), which, in turn, has two significant and opposite effects on the *Polity*2 measure of democracy. The indirect effect suggests that one in every 100 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 (Eq. 2, column 8). This estimate supports the first component of Hypothesis 2 on the increased likelihood of corruption following floods. We also estimate that more corruption is associated with a higher *Polity*2 score of 0.86 points (0.175×4.891) on a scale of [-10, 10], an effect that is significant at the 1% level (Eq. 3, column 9). This empirical evidence echoes the equilibrium outcome of our game-theoretic model presented in Sect. 3. Also, it corroborates the second component of Hypothesis 2.

On the other hand, rainfall-driven floods have a direct and negative effect on democracy. Our estimates of Eq. (3) in column 9 indicate that one in every 100 people affected by floods is associated with a *Polity*2 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 1 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

[16] Our sample indicates that 25% of flooding events around the world during the 1979–2009 period affected at least 1% or more of a country's population, on average.

*Polity*2 measure of democracy. Given that the indirect effects are statistically superior, it seems safe to conclude that there is a net positive change in *Polity*2 scores following extreme rainfall-driven floods.

6.2 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, lagged relationships with respect to both the direct and indirect effects are possible. 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 over a longer time horizon to sustain itself in power. To determine whether such temporal effects in fact can be observed, 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 *Polity*2 at time *t*. Notably, in Models 4.1 to 4.4 of Table 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 greater corruption following 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 aid for relief and recovery is exhausted once the disaster-driven resource windfall window is closed. This effect contrasts with the endemic, longer-lived corruption effect, which typically is 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 its benefits. Overall, our result uncovers a new finding in this line of research, namely that if flood relief-related expropriations are observed by citizens, they may demand political reform over many years (rather than only contemporaneously), but that the immediate demand component is relatively short-lived, as is the resource windfall and the consequent expropriation that ensues.[17]

Lagged direct 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 time in power; however, we do not read much into this evidence owing to its weaker statistical significance.

6.3 The validity of the exclusion restrictions

As discussed in Sect. 5, the validity of the exclusion restriction is critical within our system-of-equations context, i.e., extreme rainfall should have no systematic effects on country's level of corruption beyond that which it exerts on flood severity. Notwithstanding our very

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

Table 5 Neighbors' extreme rainfall: Checking the exclusion restrictions

Variables	5.1: Sample with available neighbors' extreme rainfall data			5.2: Neighbours' extreme rainfall weighted by population			5.3: Neighbours' extreme rainfall weighted by GDP		
	No. of flood-affected persons in every 100 people (1)	PRS corruption index (2)	Polity2 (3)	No. of flood-affected persons in every 100 people (4)	PRS corruption index (5)	Polity2 (6)	No. of flood-affected persons in every 100 people (7)	PRS corruption index (8)	Polity2 (9)
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 (0.080)	−1.021 (2.023)	−0.078 (0.106)			
Log neighbors' extreme rainfall weighted by GDP							0.072 (0.073)	−1.024 (2.021)	−0.015 (0.098)

Table 5 continued

Variables	5.1: Sample with available neighbors' extreme rainfall data			5.2: Neighbours' extreme rainfall weighted by population			5.3: Neighbours' extreme rainfall weighted by GDP		
	No. of flood-affected persons in every 100 people (1)	PRS corruption index (2)	Polity2 (3)	No. of flood-affected persons in every 100 people (4)	PRS corruption index (5)	Polity2 (6)	No. of flood-affected persons in every 100 people (7)	PRS corruption index (8)	Polity2 (9)
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	1973	1973	1973	1973	1973	1973	1973	1973	1973

See the notes to Table 3

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 responses in neighboring 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 challenge our results by producing a consistent pattern of extreme rainfall catastrophes shared by neighboring countries. Nevertheless, we undertake a formal step to address this issue by controlling for neighbors' extreme rainfall events (as weighted by neighbors' populations). If neighbors' extreme rainfalls affect a country's income and democracy over and above its own incidents, then our exclusion restrictions may be violated. Nonetheless, Table 5 shows neighbors' extreme rainfall to be insignificant in all of our models.

Another concern is that the income of neighboring countries ($logNY$) may influence *Polity*2 in Eq. (3) 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 Eqs. (2) and (3); 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 excluded conclusively, our restrictive empirical design seems to eliminate significant indirect correlations that might otherwise jeopardize identification of the system.

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 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 already are 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.

This paper hypothesizes two possible effects between extreme rainfall-driven flooding incidents and democracy—a direct repression effect and an indirect effect through corruption. Scholarly literature is relatively unambiguous about the authoritarian tendencies prompted by chaos, plunder, and plight caused by natural disasters, at least in somewhat authoritarian countries. Hence, we expect the direct effect of flooding to be less democracy. In terms of the indirect effect, the literature is also clear that flooding can increase the scope of public sector corruption, but provides mixed arguments about the possible role played by flood-induced corruption on democracy.

Consequently, this paper first unpacks the indirect effect, i.e., the relationship between flood-induced corruption and 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 emergency relief and the voters' subsequent reaction to the government's choice. The model's 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 reelection. 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.

The paper next undertakes a detailed empirical investigation using a new measure of extreme rainfall covering a sample of 130 countries over the 1979–2009 period. Our findings strongly indicate that extreme rainfall-driven flood incidents result in two significant but opposing effects on democracy. On one hand, extreme rainfall-driven floods increase corruption in the post-disaster emergency response and recovery efforts, which, in turn, leads to 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.

Overall, this study traces two different components of political change that occur in the aftermath of flooding events: a direct effect leading to a greater autocratic tendency in the incumbent regime, which we interpret to be caused by a repressive governmental response in disaster management and an indirect effect through which more disaster-related corruption results in more democracy following the government's reelection. Our finding that the repression-led autocratic tendency is dominated empirically by corruption-induced democracy 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 corruption emerges during the distribution of relief. Governments can overcome this challenge by offering to be more democratic in the future.

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Appendix 1

See Table 6.

Table 6 Total number of nodes used in deriving extreme rainfall estimates in each country

Country	Nodes	Country	Nodes	Country	Nodes
Afghanistan	9	Guinea Bissau	1	Paraguay	5
Algeria	35	Guyana	3	Peru	16
Angola	18	Hungary	1	Philippines	4
Argentina	44	India	45	Poland	6
Australia	112	Indonesia	23	Portugal	1
Azerbaijan	2	Iran Islam Rep	26	Romania	3
Bangladesh	2	Iraq	5	Russia	467
Belarus	4	Ireland	2	Saudi Arabia	28
Belgium	1	Italy	5	Senegal	3
Benin	1	Ivory Coast	4	Serbia	1
Bolivia	17	Japan	6	Sierra Leone	1
Bosnia-Herzegovina	1	Jordan	1	Slovakia	2
Botswana	9	Kazakhstan	52	Slovenia	1
Brazil	110	Kenya	8	Somalia	8
Bulgaria	2	Korea Rep	1	South Africa	17
Burkina Faso	3	Kyrgyzstan	3	Spain	7
Cambodia	3	Lao P Dem Rep	3	Sri Lanka	1
Cameroon	5	Latvia	2	Sudan	27
Canada	268	Lesotho	1	Swaziland	1
Central African Rep	7	Liberia	1	Sweden	13
Chad	19	Libyan Arab Jamah	23	Switzerland	2
Chile	14	Lithuania	1	Syrian Arab Rep	4
China P Rep	153	Macedonia FRY	1	Tajikistan	3
Colombia	14	Madagascar	8	Tanzania Uni Rep	14
Congo	4	Malawi	2	Thailand	6
Croatia	2	Malaysia	3	Togo	2
Czech Rep	1	Mali	17	Tunisia	2
Denmark	1	Mauritania	15	Turkey	13
Dominican Rep	2	Mexico	31	Turkmenistan	8
Ecuador	4	Moldova Rep	1	Uganda	4
Egypt	14	Mongolia	31	Ukraine	13
El Salvador	1	Morocco	10	United Arab Emirates	1
Equatorial Guinea	2	Mozambique	9	United Kingdom	4
Eritrea	2	Namibia	11	United States	176
Estonia	2	Nepal	2	Uruguay	3
Ethiopia	14	New Zealand	5	Uzbekistan	7
Finland	11	Nicaragua	2	Venezuela	12
France	11	Niger	16	Viet Nam	4
Gabon	3	Nigeria	11	Yemen	7
Georgia	2	Norway	13	Zaire/Congo Dem Rep	30
Germany	10	Oman	5	Zambia	10
Ghana	2	Pakistan	13	Zimbabwe	6
Greece	3	Panama	1		
Guinea	4	Papua New Guinea	6		

Appendix 2

See Table 7.

Table 7 Data definitions and sources

Variable	Description	Source
Extreme rain	Extreme rainfall measure: constructed by comparing the actual volume of monthly total rainfall in each month with the 90th percentile of monthly total rainfall that occurred in any month in the last 30 years; *see* Sect. 3 for further details	GPCP dataset, available at http://precip.gsfc.nasa.gov
Flood	No. of affected people in floods: this is the total number of people injured, homeless or affected by flood incidents that occurred in a given year in each country	EM-DAT dataset (CRED 2011)
NY	Average GDP of neighbouring countries: constructed using real GDP per capita dataset from PWT	Calculated from PWT (Heston et al. 2011)
Corruption	The rescaled PRS measure of corruption indices ranging from 0 to 6 (i.e., higher values refer to higher level of political risk involved in corruption)	International country risk guide (PRS-ICRG 2007)
*Polity*2	Polity measure of democracy: the revised combined Polity2 score; the maximum range of this measure is –10 to 10. Positive values indicate an improvement in democracy, while negative indicate a deterioration	Polity IV project (Marshall and Jaggers 2005)
NP	Average Polity2 score of neighbouring countries: constructed using Polity2 measure of democracy	Calculated from Polity IV project
Neighbours' extreme rainfall	Average extreme rainfall of neighbouring countries: constructed using the extreme rainfall dataset from GPCP	Calculated from GPCP dataset
Population	Total population, in thousands	PWT (Heston et al. 2011)

Appendix 3: Data on other variables

The Polity IV project revised combined Polity score (i.e., Polity2), ranging from −10 to 10 (i.e., autocracy to democracy), is taken as the measure of democracy (Marshall and Jaggers 2005). It estimates the level of democracy based on the competitiveness of political participation, the openness and competitiveness of executive recruitment and constraints on the executives. In spite of having several methodological shortcomings, the Polity2 score is—arguably—the most accurate measure of democracy, thus is widely used in the literature (see Glaeser et al. 2004).

Our income measure—that is, real GDP per capita—and the population size are sourced from the *Penn World Table*s (PWT), version 7.0 (Heston et al. 2011), which provides data for the period 1950– 2009. The agriculture value-added data—measured as the share of the population for each country in a given year—are from the UN Statistical Division (UNSTAT, 2012).[18]

[18] We take the natural log of the per capita agricultural output to maintain the underlying data distribution uniformly symmetric.

The corruption index dataset—ranging from 0 to 6, in which higher values refer to higher political risk of involvement in corruption—are obtained from the PRS's *International country risk guide* (see PRS-ICRG 2007). This PRS measure captures the corruption within the political system that is a threat to foreign investment by distorting the economic and financial environment, reducing the efficiency of government and business by enabling people to assume positions of power through patronage rather than ability, and introducing inherent instability into the political process (PRS-ICRG 2007).

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