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Home bias in humanitarian aid: The role of regional favoritism in the allocation of international disaster relief

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Abstract

This paper investigates whether regional favoritism shapes humanitarian aid flows. Using a rich and unique dataset derived from reports of the Office of US Foreign Disaster Assistance (OFDA), we show that substantially larger amounts of aid are disbursed when natural disasters hit the birth region of the recipient countries' political leader. While we find no evidence that US commercial or political interests affect the size of this home bias, the bias is stronger in countries with a weaker bureaucracy and governance, suggesting the absence of effective safeguards in the allocation of aid.

Keywords: humanitarian aid, natural disasters, regional favoritism, birth regions

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1. Introduction

The principle of impartiality in the allocation of humanitarian aid is firmly established in international law (Persson 2004). In spite of this, anecdotal evidence suggesting that politically important sub-national regions receive favorable treatment is easy to find. According to policy reports by the Red Cross and Red Crescent Societies (Klynman et al., 2007) and the International Dalit Solidarity Network (2013), power relations at the community level within recipient countries distort the allocation of humanitarian aid. In this paper, we provide the first systematic investigation of whether and to what extent humanitarian aid is indeed impartial with respect to recipient country politics. We focus on the birth regions of recipient country leaders and investigate whether they are more likely to receive (larger) support when being hit by exogenous rapid-onset natural disasters.

The importance of national leaders' birth regions for the allocation of funds under their control has been demonstrated in previous work, most notably in Hodler and Raschky (2014). Investigating one potential channel, Dreher et al. (2019) show that recipient leaders channel foreign aid to their birth regions to the extent that the donor does not put strings on how these funds are allocated, but not otherwise. We thus consider the focus on birth regions to be a suitable test of the impartiality principle in the allocation of humanitarian aid. Given the direct connection of such assistance with humanitarian suffering, the examination of such political economy factors is of paramount importance.[1]

We examine whether recipient country leaders can channel humanitarian aid in line with their personal interests – with the potential to influence domestic political equilibria – and whether and to what extent commercial and political relations with the donor facilitate their

[1] Natural disasters constitute a major challenge for human welfare. In the 1964-2017 period, they have reportedly killed more than five million people across the globe (Guha-Sapir et al., 2018). Furthermore, natural disasters exert negative effects on the purchasing power of disaster victims (Heinen et al., 2019), economic growth (Felbermayr and Gröschl, 2014) and on the long-run development of human capital (Caruso, 2017; Dinkelman, 2017) and income (Karbownik and Wray, 2019). As climate scientists predict a substantial increase in both the frequency and intensity of natural disasters in the near future, this type of aid is likely to further gain in importance for human welfare. What is more, climate-related risks are projected to be disproportionately concentrated in already vulnerable countries with low response capacities (IPCC, 2018).

abuse. Specifically, we investigate the allocation of humanitarian aid from the United States for 6,228 rapid-onset natural disasters that have hit 50 countries over the 1964-2017 period. We derive these rich and unique data on disaster relief from annual reports issued by the Office of US Foreign Disaster Assistance (OFDA) – the US agency responsible for providing disaster relief overseas. OFDA responds to an average of 65 disasters in more than 50 countries per year (USAID, 2018a); the United States have been by far the biggest donor of humanitarian aid. In the 1972-2017 period, they financed more than 40% of the humanitarian assistance of the countries that report to the OECD's Development Assistance Committee (DAC) (OECD, 2019).

We employ three strategies to address endogeneity and identify the causal effects of leaders' birth regions on the allocation of humanitarian aid.[2] First, we control for a range of observable characteristics of the affected sub-national area. This type of specification allows us to adjust for the most obvious sources of confounding. However, unobserved omitted variables could potentially still bias estimates. In a second step, we therefore include disaster-area fixed effects, limiting the analysis to identical areas that have been hit by multiple disasters, while having experienced changes in their birth region status over time. In this restrictive setting all time-invariant unobserved heterogeneity is controlled for, allowing us to further increase the internal validity of our estimates.

As a third empirical approach, we run placebo regressions that test whether disasters hitting regions that were the birth region in the previous or subsequent year of the disaster, but not during the time of the disaster itself, receive similar treatment compared to disasters hitting contemporaneous birth regions. In comparing these points in time, any unobserved characteristics of birth regions that do not vary over a very short period are thus accounted for. We have no reason to assume that exogenous disasters should be more likely to receive funding in case they hit the birth region of a national leader,

[2] While the timing as to when a rapid-onset natural disaster hits a particular sub-national region is random, decisions on aid allocation might be endogenous. Sub-national regions connected to the government by virtue of being the political leader's birth region might differ from other regions in ways that are correlated with the need for aid. For instance, it seems plausible that regions with political ties to the government are richer and better protected against the risks arising from natural disasters compared to areas populated by weaker groups. In such a case, our estimate of how regional favoritism affects the allocation of aid could be biased.

compared to disasters that hit the same region in the years directly before or after the leader assumes power. Comparing these years thus allows us to derive a causal estimate of the importance of birth region favoritism in a scenario of urgent humanitarian need.

Our results suggest that birth region-related favoritism exerts a strong and robust influence on humanitarian aid, increasing the *amounts* of US-provided disaster relief by 45% to 85% in our main specifications. In contrast, we do not observe any systematic effects on the *probability* of receiving US-provided disaster relief, which can be plausibly explained by the structure of OFDA's decision-making process. We do not find evidence that the United States' political or commercial interests in a country hit by a disaster affect the size of the home bias. To the contrary, recipient-country characteristics in which leaders should find it easier to misappropriate funds – such as clientelism prevailing in public spending or low bureaucratic quality – explain a substantial share of it. What is more, providing a novel and innovative dataset on ethnic power relations, we show that the observed favoritism is not explained by ethnic ties between political leaders and the population in disaster-affected areas, but constitutes a self-sustained, independent dimension of favoritism within recipient countries.

With this paper, we mainly contribute to two strands of literature. First, and most directly, our research connects to a number of studies that investigate the determinants of disaster aid allocation across countries. According to these studies, donor political interests influence humanitarian aid (Ball and Johnson, 1996; Drury et al., 2005; Eisensee and Strömberg, 2007; Strömberg, 2007; Fink and Redaelli, 2011; Fuchs and Klann, 2012; Raschky and Schwindt, 2012; Annen and Strickland, 2017). While some of these previous studies also used individual disasters as unit of observation (rather than country-years), the political economy within *recipient* countries has largely been ignored.[3]

[3] There are two exceptions, both focusing on individual countries rather than a broader sample. One focuses on the head of government's electoral incentives, such as re-election concerns or providing support to the governing party at the national or regional level (Jayne et al., 2002; Francken et al., 2012; Kunze and Schneider, 2019; Eichenauer et al., 2019). The second investigates discrimination against individual victims of disasters. This literature shows that the probability to receive aid depends on gender, race, income, and education, among others (Broussard et al., 2014; Bolin and Kurtz, 2018).

Second, this paper contributes to the literature investigating regional favoritism. Hodler and Raschky (2014) and Dreher et al. (2019) show that country leaders' birth regions experience higher economic growth and receive more Chinese foreign aid, respectively. This literature provides the analytic background for our study. It shows that leaders of countries around the world divert resources to their birth regions, either for altruistic purposes, or political ones. However, given that disaster relief is primarily triggered by large, exogenous shocks with potentially grave humanitarian consequences, such political-economy considerations would even be more alarming, and stand in direct contrast to international law.[4]

More broadly, our results also relate to the aid allocation literature at large. Much of this literature investigates how donor political interests affect the allocation of aid at the country level (Alesina and Dollar, 2000; Kuziemko and Werker, 2006; Hoeffler and Outram, 2011; Vreeland and Dreher, 2014). Only recently, this literature has begun to investigate political motives in the allocation of aid at the sub-national level. However, due to limited data availability, previous work has focused on either single recipient countries, multilateral aid, or the allocation of Chinese development finance.[5] With this analysis, we are thus the first to investigate the effect of regional favoritism in the allocation of a Western bilateral donor for a large number of recipient countries and thus extend the literature in an important dimension. What is more, our focus on exogenous variation in recipient need caused by natural disasters facilitates the identification of causal effects compared to studies focusing on the allocation of aid more broadly.

Finally, we also contribute to the literature on ethnic power relations by providing novel data on the sub-national location of ethnic groups, which we use to separate favoritism towards ethnic regions from those towards birth regions. Unlike previous studies (e.g., De Luca et al. 2018, Anaxagorou et al., 2019), we identify the ethnic composition of sub-national populations based on census and survey data. This is an improvement over

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[4] See Carozzi and Repetto (2016), Fiva and Halse (2016), and Do et al. (2017) for additional studies investigating birth region-related favoritism. On political favoritism more broadly, see Baskaran and Hessami (2017).
[5] See Francken et al. (2012), Dionne et al. (2013), Jablonski (2014), Masaki (2018), Nunnenkamp et al. (2017), Brazys et al. (2017), Anaxagorou et al. (2019) and Dreher et al. (2019).

previous research, which is mostly based on less precise historical ethno-linguistic or expert-based maps such as *Ethnologue* data (Gordon, 2005), the *Geo-referencing of Ethnic Regions* (*GREG*) data (Weidmann et al., 2010) or *GeoEPR* – a geocoded version of the *Ethnic Power Relations* (*EPR*) dataset (Wucherpfennig et al., 2011).

We proceed as follows. Section 2 introduces our main data sources – on humanitarian aid, natural disasters, leaders' birth regions – as well as our control variables, and discusses the methods used to construct our measures. Section 3 discusses descriptive statistics, while Section 4 explains our method of estimation. We show the main results in Section 5 and our analyses of whether US-commercial and political interests drive the effect in Section 6. Section 7 presents extensions to the main analyses, while the final Section 8 discusses the policy implications of our research.

2. Data sources and variables

Disaster Aid

Three main data sources have previously been used to study the effect of natural disasters on aid. One group of papers relies on data that donor governments report to the OECD's DAC, which includes entries for emergency relief and food aid, among others. While these data have the advantage of being easily available for the major Western donors organized in the DAC, using them comes at a cost. As DAC data do not exclusively focus on disaster relief, but also on crisis prevention, and emergencies other than disasters, such aid cannot directly be attributed to individual disasters (Fink and Redaelli, 2011). Given that it is thus not possible to attribute the aid flows to sub-national regions in aid-receiving countries, DAC data are not suitable to address our research questions.

A second set of papers relies on data provided by the Financial Tracking Service (FTS) managed by the UN Office for the Coordination of Humanitarian Affairs (OCHA). One of its main advantages consists of its wider coverage of donor countries. These data cover nearly all donor countries in the world rather than just the set of mainly Western donors that report to the DAC. Contrary to the DAC data – which are at the recipient-year level –

the FTS provides aid information for disaster appeals. These data come, however, with the disadvantage that reporting to FTS is voluntary, potentially giving rise to underreporting (Harmer and Cotterrell, 2005; Raschky and Schwindt, 2012). Moreover, parts of the aid reported there cannot be attributed to specific disasters. While previous work making use of FTS data was restricted to the 1992-2004 period (Fink and Radaelli, 2011), the share of contributions not assigned to a specific disaster is substantially higher in more recent years, creating the risk of measurement error for our analysis.[6] Finally, the lack of a common standard by which individual donors report their aid contributions makes it difficult to compare aid across donors. For example, overvalued in-kind contributions could lead to over-reporting of aid (Harmer and Cotterrell, 2005).

The third group of papers focuses on the United States as donor exclusively, using data from the US Office for Foreign Disaster Assistance (OFDA). OFDA is part of the US Agency for International Development (USAID) and is the lead agency responsible for international disaster relief (Drury et al., 2005; Eisensee and Strömberg, 2007; Fink and Radaelli, 2011; Margesson, 2013; Kevlihan et al., 2014).[7] The United States are by far the largest provider of disaster relief, both in terms of the number of supported disasters and regarding the amounts of aid provided. For the 1972-2017 period, the United States financed more than 40% of the humanitarian assistance provided by countries of the DAC. (OECD, 2019). The key advantage of OFDA data compared to the previously mentioned data sources consists of the agency providing detailed and complete annual reports for each fiscal year since 1964, allowing us to match individual contributions to specific disasters without ambiguity. This rather long time frame combined with the reliability and completeness of aid data makes OFDA the most suitable data source for the research question at hand.

[6] According to personal correspondence with FTS staff, one reason for the increase in unassigned contributions is a lack of resources to properly categorize all disasters (email from August 10th, 2017).
[7] The USAID (2005: 10) defines disaster aid as "[i]mmediate, life sustaining assistance provided to disaster victims." It is given based "upon the written determination that a disaster exists in the host country which meets three criteria: it is of a magnitude with which the affected community cannot cope; recognized representatives of the affected population desire the assistance; and it is in the USG's [United States Government's] interests to respond" (USAID, 2005: 5).

We extract aid flows from OFDA's annual reports for the fiscal years 1990 to 2017 and transform them to constant 2017 US Dollars (OFDA, 1990-2017). For the 1964-1989 period, we use data provided to us by Cooper Drury who previously conducted research based on data from OFDA's annual reports (Drury et al., 2005).[8] Besides OFDA, there are other US agencies that allocate disaster assistance, most notably the Office of Food for Peace (also part of USAID) and the US Department of Defense (Margesson, 2013). Thanks to its chief role for US disaster assistance, OFDA collaborates closely with these agencies and provides approximate numbers for their aid contributions for the sub-period 1964 to 2004.[9] While our main analysis focuses on the full period (1964-2017), we show in a test for robustness that our key results extend to the aid provided by the full range of US agencies using the 1964 to 2004 sub-period.

Natural Disasters

We take data on natural disasters from the EM-DAT international disaster database (Guha-Sapir et al., 2018), which was assembled by the University of Louvain's *Centre of Research on the Epidemiology of Disasters* (*CRED*). This is the most comprehensive list of disasters available, comprising more than 22,000 disasters from the year 1900 to the present. EM-DAT includes disasters that meet at least one of the following criteria: At least ten people are reported as killed, at least one hundred people are reported to be affected, a state of emergency has been declared, or a call for international assistance has been issued. They provide disaster-specific information on the type of disaster, the number of people killed, missing and presumed dead, and the number of people affected (EM-DAT, 2018b).[10] Conveniently, EM-DAT also includes the sub-national location of the disaster for the first administrative levels or lower.[11]

[8] All annual reports (with the exception of the 1974-1982 period) are available for download from the USAID Development Experience Clearinghouse (USAID, 2018b).

[9] In this time period, OFDA aid flows represent on average 76% of all US disaster relief.

[10] EM-DAT draws from a number of sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies (EM-DAT, 2018a).

[11] Sub-national regions at the first administrative level (ADM1) typically are departments, provinces or states; regions at the second administrative level (ADM2) include districts or municipalities, among others. Whenever a change in the admin boundaries occurred over time, we consider the modern counterparts of reported administrative areas. We provide further details in Table A1. Note that out of 7,318 disasters, 880 disasters (of which only 60 received OFDA aid) are not considered in the analysis due to imprecise location information. Moreover, disasters in Vietnam during the Vietnam War are excluded.

For our analysis, we include the 50 countries that are most frequently affected by rapid-onset disasters (floods, storms, earthquakes, epidemics, landslides, extreme temperatures, volcanic activity, wildfires, dry mass movements and insect infestations) over the 1964-2017 period.[12] We follow Fink and Redaelli (2011) in limiting the scope of the analysis to rapid-onset disasters, whose timing is rather random and therefore occur unexpectedly. By contrast, the timing and particularly the duration of slowly evolving catastrophes such as droughts, famines or complex emergencies might introduce endogeneity concerns.[13] We merge the EM-DAT list of disasters with disaster-specific aid data from OFDA reports based on the timing and location of disasters. EM-DAT disasters not mentioned in the OFDA reports are assumed to not have received aid.[14]

Leaders' birth regions

To identify birth regions of the countries' political leaders, we make use of the latest version of the Archigos database of leaders such as presidents, prime ministers, or religious leaders, depending on the political system (Goemans et al., 2009; Archigos, 2018). We complement these data with birthplace information acquired through online search.[15] While leader birth regions are often also available at the ADM2 level, we focus on ADM1 birth regions, as EM-DAT does not always provide a comprehensive list of affected ADM2 areas. Our explanatory variable of interest is then constructed as a binary indicator equal to one if any of the disaster-specific locations listed by EM-DAT was the birth region of the political leader at the time of the disaster, and zero otherwise.[16]

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[12] Given that we focus on within-country variation in disaster locations, increasing the sample beyond the 50 most frequently affected countries would hardly increase the degrees of freedom. Moreover, the following advanced economies with a high number of natural disasters, which rarely appear in OFDA reports, were not included in the sample: Australia, Canada, France, Hong Kong, Italy, Japan, New Zealand, Russia, South Korea, Spain, Taiwan, and United Kingdom. We exclude Algeria due to a lack of variation in the birth region status of disaster-affected areas and Somalia due to the uncertain governmental control over national territory.

[13] Including disasters that are driven by such dynamics would substantially increase the complexity of the analysis and its interpretation as the United States may adjust its aid depending on how a disaster evolved. For the same reason, we do not include technical disasters.

[14] We exclude observations for which matching was not possible due to ambiguous information on timing, and location and due to ambiguous information on aid flows. As a consequence, 79 disasters remain unmatched and hence drop out from the sample.

[15] We provide an overview of all relevant leaders and their birth regions in Table A1.

[16] For most disasters reported by EM-DAT, start dates and end dates are identical or very close to each other. In the uncommon event where start and end dates differ and leaders change in between, we code the binary indicator as equal to one if any of the leaders' birth regions was hit. We use the same approach

Control variables

To address the concern that regions affected by natural disasters may differ from other regions in ways that are correlated with birth region status and aid flows, we construct a range of control variables reflecting local area characteristics. In particular, we suspect that birth regions are richer, more populated (affecting the economic damage and number of casualties created by disasters) and easier to access (facilitating disaster relief). For the construction of control variables for population density, nighttime light intensity, barren land and ruggedness, we match the disaster locations indicated by EM-DAT with grid maps and calculate zonal statistics using a Geographic Information Systems software. For the case of multi-location disasters, we weight locations by their area.[17]

As a measure for population concentration, we use the above procedure to construct a continuous variable for average population density per square kilometer in the year 2015.[18] Moreover, we control for the population size in major cities of affected areas for the entire time period of analysis, based on data from the UN World Urbanization Prospects (UN, 2018). We lag values by one year, rescaled to ten million inhabitants.[19]

For economic activity, we use average annual cloud-free night time light intensity maps in combination with population figures to construct a measure of average night time light intensity per capita. This variable aims to capture economic activity conditional on population density. For that purpose, we use data from the National Oceanic and Atmospheric Administration (NOAA, n.d.). As night time lights are highly volatile across years, we exploit the availability of maps for multiple years (1992 to 2013) and take averages across time before taking averages across administrative regions. This approach brings the advantage of reducing the influence of very cloudy years, in which satellites can only measure night time light emissions during a limited number of days.[20]

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for the rare case that only the month and year of the disaster are reported and a leader change happens to occur in the respective month.

[17] To increase precision, we exploit information at the ADM2-level whenever available.

[18] We rescale the variable to 1,000 people per square kilometer. For the vast majority of countries, we use data from the WorldPop project (Tatem, 2017). Where these are unavailable, we use SEDAC (CIESIN, 2017).

[19] The cities included in the dataset are those with more than 300,000 inhabitants in the year 2018.

[20] The fact that we take averages across time brings the disadvantage that we cannot use lagged night time light intensity which would limit endogeneity concerns. However, the required satellite data are unavailable

Further variables that control for the economic or strategic relevance of the affected areas are the percentage of barren land, the number of ports, the number of nuclear plants and a binary indicator for disasters hitting the capital city. The barren land variable is based on the GlobCover 2009 grid map, which captures the share of land classified as bare land in the disaster-affected areas (Arino et al., 2012). Data for the number of large ports and nuclear plants comes from the World Port Index of the US National Geospatial Intelligence Agency (NGIA, 2017) and the World Nuclear Association (WNA, 2017), respectively.[21]

To proxy for accessibility, we measure ruggedness with the so-called Terrain Ruggedness Index, which was initially developed by Riley et al. (1999) and constitutes a fine-grained measure for average differences in elevation per 30 arc seconds grid cell. We use pre-constructed grid cell-level data by Nunn and Puga (2012) and take averages across grid cells within disaster areas. Similar to them, we scale the index such that it represents average elevation differences in hundreds of meters.

3. Data description

Table 1 shows descriptive statistics by disaster type. The 50 countries included in our sample were hit by 6,228 natural disasters, 13.4% of which received disaster relief from OFDA. On average, 360 persons were reported dead and the average disaster with positive aid flows received approximately 1.78 million 2017 US dollars. Funding shows high variation as indicated by the large standard deviations in parentheses. In rare cases, OFDA donated aid to multiple disasters at once. We treat these cases as one event and assign the disaster type "multiple" if these disasters were of different types.

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for years before 1992 and we consider measurement error a more severe problem. Moreover, results (available on request) remain close to identical when night light intensity and/or population density are dropped from the analysis.

[21] We use one-year lags for the number of nuclear plants. The number of ports does not vary over time in our sample period.

Table 1. Disaster impact and emergency relief, 50 countries, 1964-2017

Disaster type	Frequency	Average number of casualties (SD)	Percentage funded	Average funding in 1,000s, 2017 US dollars (SD)
Earthquake	761	1,350.1 (13,058.8)	18.4	4,850.8 (28,916.2)
Epidemic	608	194.0 (600.6)	5.9	865.8 (3,666.2)
Extreme temperature	186	134.0 (315.5)	1.6	1,732.6 (2,798.0)
Flood	2554	79.7 (654.5)	13.9	1,047.5 (12,695.0)
Insect infestation	16	0.0 (0.0)	37.5	537.3 (551.8)
Landslide	452	70.6 (185.3)	7.1	137.1 (215.3)
Mass movement (dry)	24	77.3 (86.8)	12.5	46.7 (7.0)
Storm	1371	583.9 (9,749.8)	13.8	1,665.4 (5,220.5)
Volcanic activity	134	183.2 (1,883.0)	22.4	905.7 (1,947.9)
Wildfire	98	8.0 (22.6)	18.4	485.2 (996.6)
Multiple	24	367.3 (397.9)	100.0	1,641.8 (3,048.3)
All disasters	6,228	360.0 (6,495.9)	13.4	1,776.5 (14,720.2)

Notes: Standard deviations in parentheses. Average funding includes only aid provided by OFDA (rather than all US government agencies). We exclude disasters without any funding from this average.

Analyzing the table by disaster type, important differences become visible. First, certain disasters are substantially more frequent than others. For instance, more than half of the sample comprises of storms and flood events, while insect infestations are rare. Disasters belonging to the categories of insect infestation, volcanic activity, earthquake and wildfire are more likely to receive funding. Among those disasters with funding, earthquakes, extreme temperatures and storms receive the larger aid amounts on average. It should be noted however that there is a large variation in the granted aid amounts within most disaster types.

Table 2. Summary statistics by country

Country	Disasters	Average number of casualties	Percentage hit leader's birth region	Percentage funded	Average funding in 1,000s (2017 USD)
Afghanistan	150	137.7	7.3	5.3	509.9
Angola	55	109.3	41.8	9.1	293.6
Argentina	93	11.3	31.2	12.9	169.8
Bangladesh	223	802.4	29.1	4.5	2,413.4
Bolivia	67	25.1	38.8	34.3	232.2
Brazil	175	60.5	17.1	13.7	147.3
Chile	77	36.8	35.1	16.9	1,453.0
China	748	586.0	9.5	4.1	311.9
Colombia	143	212.3	19.6	14.0	771.2
Costa Rica	50	9.3	24.0	52.0	392.3
Cuba	49	4.3	34.7	8.2	519.3
DR Congo	118	89.8	16.1	8.5	923.3
Dom. Rep.	57	31.5	33.3	21.1	816.6
Ecuador	77	108.3	28.6	28.6	621.4
El Salvador	37	94.2	45.9	32.4	2,196.3
Ethiopia	59	44.5	27.1	10.2	173.7
Greece	69	9.0	24.6	13.0	504.9
Guatemala	77	339.2	35.1	16.9	634.7
Haiti	93	2,575.5	47.3	23.7	19,524.0
Honduras	52	232.0	26.9	28.8	687.3
India	535	326.8	8.2	7.9	1,081.4
Indonesia	415	72.3	10.6	12.3	474.6
Iran	159	744.1	6.9	5.0	2,076.1
Kenya	81	56.5	21.0	4.9	1,914.1
Madagascar	56	80.8	44.6	42.9	580.6
Malawi	40	32.5	22.5	22.5	366.4
Malaysia	60	15.6	20.0	11.7	415.8
Mexico	208	77.8	4.8	11.1	746.4
Mozambique	70	59.7	38.6	22.9	1,922.3
Myanmar	55	2,569.9	20.0	21.8	3,638.3
Nepal	83	231.3	38.6	16.9	2,676.2
Nicaragua	52	19.5	23.1	40.4	304.0
Niger	61	149.6	39.3	18.0	156.4
Nigeria	108	249.3	10.2	4.6	147.2
Pakistan	185	2,418.6	17.8	16.2	12,196.3
Panama	46	7.2	34.8	28.3	113.0
Papua N.G.	54	60.5	5.6	18.5	160.5
Peru	131	595.9	21.4	22.1	1,248.6
Philippines	450	123.7	22.0	14.7	1,291.7
Romania	53	48.1	34.0	20.8	2,383.4
South Africa	84	24.0	27.4	7.1	85.6

Table 2. Summary statistics by country (continued)

Country	Disasters	Average number of casualties	Percentage hit leader's birth region	Percentage funded	Average funding in 1,000s (2017 USD)
Sri Lanka	73	55.3	41.1	23.3	456.9
Sudan	75	118.7	18.7	22.7	1,063.0
Tajikistan	57	9.7	43.9	28.1	543.0
Tanzania	70	64.8	8.6	10.0	64.2
Thailand	99	41.6	12.1	15.2	223.0
Turkey	121	277.8	14.0	12.4	3,733.1
Uganda	61	30.6	4.9	11.5	122.4
Venezuela	39	794.7	10.3	17.9	564.5
Vietnam	178	87.6	11.2	14.6	283.4
All disasters	6,228	360.0	18.9	13.4	1,776.5

Notes: Average funding includes only aid provided by OFDA (rather than all US government agencies). We exclude disasters without any funding from this average.

We further provide an overview of descriptive statistics for all countries in Table 2.[22] Overall, there is substantial heterogeneity in the indicators. The number of disasters included in the sample ranges from 37 in El Salvador to 748 in China, while the percentage of funded disasters varies between 4.1% (China) and 52% (Costa Rica).[23] There are further significant differences in the percentages of disasters hitting the leader's birth region, with values ranging from 4.8% (Mexico) to 47.3% (Haiti). Finally, the included disasters are on average deadliest in Myanmar, with a mean of 2,569.9 casualties.

4. Empirical strategy

We estimate a range of regression models to test for birth region-related favoritism in the provision of disaster relief. We follow Fink and Redaelli (2011) and Raschky and Schwindt (2012) by estimating this relationship as a two-step process. The first stage of the aid allocation model captures whether or not a disaster is funded; our dependent variable Y_{ect} is thus binary and takes the value of one if any aid is granted for disaster e that took place

[22] We provide descriptive statistics for the control variables in Table A2.
[23] These figures do not involve funding practices of the United States for disaster types that are not included in this analysis. Especially for African countries, complex emergencies and droughts are salient and receive generous support from the United States.

in year t in recipient country c. In the second stage, the outcome is the amount of OFDA aid that was disbursed for a certain disaster, in logged 2017 US Dollars. Given the structure of the dataset, we estimate regressions at the disaster level rather than at the regional level. As a starting point, our empirical models are thus of the following form:

$$Y_{ect} = \beta_1 birth_{ect} + \beta_2 X_{ect} + \gamma_c + \theta_e + \delta_t + \varepsilon_{ect}. \tag{1}$$

In all specifications, $birth_{ect}$ is a binary indicator that is equal to one if any ADM1 area hit by a disaster is the birth region of the leader governing the country at the time of the disaster, and zero otherwise. The vector of control variables X_{ect} captures local area characteristics as discussed in Section 2. Note that while some of the controls are constructed with time-invariant input data, they still vary between country-specific disasters to the extent that disasters hit different areas. Moreover, we control for fixed effects on the country (γ_c), disaster-type (θ_e) and year (δ_t) levels. In a further specification, we add the number of casualties reported by EM-DAT as a proxy for disaster magnitude. This variable should be interpreted with caution, as even though we are limiting the focus to rapid-onset disasters, the number of casualties might arguably be endogenous to disaster aid.[24] We cluster standard errors at the country level.

In a more restrictive model, we then replace all control variables by disaster-area fixed effects, thus restricting the analysis to disasters that hit the same ADM1 areas with alternating birth region status over time. By comparing disasters hitting the exact same ADM1 areas, this specification brings the major advantage of allowing us to control for all factors that do not vary at the ADM1-level over time. That being said, the inclusion of restrictive fixed effects can reduce the signal-to-noise ratio, making results more sensitive to individual observations.

[24] Given the potential endogeneity of disaster magnitude, we do not use this variable in Sections 6 and 7. Results are however highly similar and are available on request.

As a third identification strategy, we therefore introduce a placebo model with an alternative exposure variable (henceforth "placebo") taking the value of one for disasters that hit regions that were birth regions in the previous or subsequent period but not during the disaster, and zero otherwise.[25] We thereby exploit a discontinuity introduced by leader changes. While new leaders may have been born in a different region than their predecessors, introducing a sudden change in the birth region status of affected regions, changes in unobserved confounding variables are unlikely to simultaneously exhibit discontinuities even if they vary over time. Regions that are the birthplace of a leader who just lost power or will gain power in the very near future should therefore exhibit the same underlying traits as the contemporaneous leader's birth region. The model is hence able to control for both time-invariant and time-variant unobserved heterogeneity.[26] A statistically significant coefficient for the placebo would thus indicate that our identification strategy might suffer from omitted variables bias. Differences between our variable of interest and the placebo can be understood as the bias-corrected net effect of disasters hitting the birth region of the current leader.[27]

5. Main results

We begin by examining whether disasters hitting the birth region of the country's leader have a higher probability of receiving humanitarian aid than disasters hitting non-birth regions. In Table 3, the dependent variable in all columns takes the value of one if the disaster received any aid and zero otherwise.

[25] We define previous and subsequent periods as one year before the start date and one year after the end date of disasters, respectively. For observations with missing days or days and months, we assumed the 15th of each month and the 1st of July as start and end dates, respectively.
[26] This placebo model is particularly powerful in the context of rapid-onset natural disasters, given their random timing.
[27] This interpretation abstracts from the possibility that leaders who just lost or are about to gain de jure power may already/still hold a certain degree of de facto power. Therefore, the placebo model, strictly speaking, provides a falsification test, as, with sufficient power, a lack of significance for the placebo coefficient rules out the discussed form of omitted variable bias but a significant coefficient does not prove with full certainty that omitted variable bias is present.

Table 3. Birth region effect on the probability to receive humanitarian aid

	(1) *Any funding*	(2) *Any funding*	(3) *Any funding*	(4) *Any funding*	(5) *Any funding*
Birth region	0.050***	0.022	0.026*	0.027**	-0.031
	(0.015)	(0.014)	(0.013)	(0.013)	(0.030)
Economic/strategic importance					
% barren land		0.000	0.001*	0.001*	
		(0.000)	(0.000)	(0.000)	
# ports		0.032**	0.022*	0.022*	
		(0.013)	(0.011)	(0.011)	
# nuclear plants		-0.006***	-0.003*	-0.003*	
		(0.002)	(0.002)	(0.001)	
Capital city		0.044***	0.048***	0.046***	
		(0.013)	(0.014)	(0.014)	
Nightlight p.c.		-0.070*	-0.029	-0.028	
		(0.041)	(0.047)	(0.047)	
Population					
Pop. density		-0.005**	-0.007***	-0.006***	
		(0.002)	(0.002)	(0.002)	
City population		0.005***	0.011***	0.011***	
		(0.002)	(0.002)	(0.002)	
Accessibility					
Ruggedness		-0.008*	-0.003	-0.002	
		(0.004)	(0.004)	(0.004)	
Magnitude					
# deaths (in 1,000s)				0.004***	
				(0.001)	
Fixed effects					
Country	X	X	X	X	
Disaster type		X	X	X	
Year			X	X	
Disaster area					X
Observations	6,228	6,228	6,228	6,228	6,228
R^2	0.067	0.114	0.183	0.188	0.618

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses. The sample consists of 50 countries over the 1964-2017 period. The dependent variable is a binary indicator taking the value of one if the disaster was granted any funding and zero otherwise. The variable birth region takes the value of one for disasters that hit the birth region of the country leader and zero otherwise.

In column 1, which adjusts for country-level fixed effects only, we find that a disaster hitting the leader's birth region significantly increases the probability to receive aid by five percentage points. However, this association turns insignificant after controlling for local area characteristics related to economic/strategic importance, population, and accessibility as well as for disaster-type fixed effects (column 2).[28] The birth region coefficient regains statistical significance once year fixed effects (column 3) and disaster magnitude (column 4) are accounted for, and reaches a magnitude of 2.6 and 2.7 percentage points, respectively. Finally, in column 5, we apply our most conservative model using disaster-area fixed effects.[29] In this specification, the coefficient is not statistically significant and turns negative. In summary, our estimates show that there is no robust evidence for systematic favoritism in the probability to receive any aid.

We next turn to the birth region effect on aid amounts in logged 2017 US-Dollars. This analysis draws upon the reduced sample of disasters with positive aid flows, which covers all 50 countries and 13.4% of all disasters in our dataset. Following the same structure as Table 3, Table 4 shows that disasters hitting leaders' birth regions receive substantially higher aid amounts than other disasters. Estimates are robust to controlling for local area characteristics, disaster-type fixed effects, year fixed effects, and disaster magnitude (columns 2 to 4). Across these specifications, the statistically significant increase in funding is of approximately 45%-85%, on average.[30] For the average disaster's funding in our sample, this corresponds to an increase by US$849,984 to US$1,506,135.

[28] The size of the population residing in cities, the number of ports and the fact that a disaster hit a nation's capital city are positively associated with the probability to receive disaster assistance across specifications. In contrast, countries are less likely to receive humanitarian aid the higher the population density and the more nuclear plants are located in disaster-affected areas. While the control variables condition on each other and may not represent causal estimates, these results suggest that nuclear plants may introduce a different geopolitical dynamic and it may not always be in the interest of the United States to extend aid if these are located in disaster areas.

[29] Given that this model reduces the variation of interest to a much narrower set of disasters, we do not include year fixed effects or other controls in order to maintain a sufficient number of degrees of freedom.

[30] Given that the outcome is logged US Dollars, the marginal effect for the binary birth region indicator expressed as percentage change in funding can be calculated as $\frac{Y(1)-Y(0)}{Y(0)} = e^{\beta_1} - 1$, where $Y(1)$ and $Y(0)$ represent the outcome with the indicator switched on and off, respectively, and β_1 being the estimated coefficient. A potential concern relates to the second stage of the aid allocation decision being subject to selection bias given that the aid amounts regression is estimated on a subsample of regions hit by disasters. As we lack a clear candidate for an excludable instrument for the first stage, the performance of the conventionally used Heckman Selection Model is limited. When we estimate a Heckman Selection Model without exclusion restriction most results are however unchanged (results available on request).

Table 4. Birth region effect on amount of received aid

	(1) *Log funding*	(2) *Log funding*	(3) *Log funding*	(4) *Log funding*	(5) *Log funding*
Birth region	0.614***	0.501***	0.368**	0.391**	0.941[*]
	(0.156)	(0.155)	(0.149)	(0.147)	(1.104)
					[0.057]
Economic/strategic importance					
% barren land		0.010**	0.005	0.009***	
		(0.004)	(0.004)	(0.003)	
# ports		-0.353**	-0.162	-0.146	
		(0.175)	(0.151)	(0.155)	
# nuclear plants		-0.190***	-0.195***	-0.164***	
		(0.057)	(0.054)	(0.060)	
Capital city		0.169	0.017	-0.003	
		(0.155)	(0.152)	(0.149)	
Nightlight p.c.		0.143	1.307	1.162	
		(3.924)	(3.716)	(3.607)	
Population					
Pop. density		0.006	0.006	0.006	
		(0.032)	(0.044)	(0.044)	
City population		0.314***	0.267***	0.235***	
		(0.049)	(0.046)	(0.049)	
Accessibility					
Ruggedness		-0.083	-0.116**	-0.101*	
		(0.055)	(0.053)	(0.053)	
Magnitude					
# deaths (in 1,000s)				0.024***	
				(0.004)	
Fixed effects					
Country	X	X	X	X	
Disaster type		X	X	X	
Year			X	X	
Disaster area					X
Observations	836	836	836	836	836
R^2	0.151	0.227	0.343	0.381	0.881

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively. Stars in brackets denote statistical significance based on clustered wild bootstrapping. Clustered standard errors in parentheses. Column 5 displays p-value based on clustered wild bootstrapping in brackets. The sample consists of 50 countries over the time period 1964-2017. The dependent variable is the disaster-specific log funding in 2017 US dollars, conditioning on having received any funding. The variable birth region takes the value of one for disasters that hit the birth region of the country leader and zero otherwise.

While these specifications already acknowledge important confounders, substantially reducing the scope of alternative interpretations for the birth region coefficient, they control for the heterogeneity of disaster-affected areas imperfectly.[31] In Column 5, we therefore introduce disaster-area fixed effects, which fully absorb all time-invariant heterogeneity

[31] As before, we find – consistently across specifications – that the number of nuclear plants is negatively associated with funding, whereas the size of the population residing in cities increases aid.

between disaster-affected areas. Note that in this restrictive model, the number of countries contributing to the point estimate is reduced to a subset of 14 countries that were affected by disasters hitting the exact same ADM1 areas multiple times with alternating birth region status. As can be seen, the coefficient is not statistically significant due to a substantial loss in precision. However, clustered standard errors are not appropriate in regressions with such a small number of clusters. For this reason, we also report a p-value based on clustered wild bootstrapping, which are more suitable for this setting (see Roodman et al., 2019). As can be seen, the birth region effect is significant at the ten percent level and increases to 156%. Interestingly, countries exhibiting this type of variation score worse in terms of governance indicators that are arguably associated with higher degrees of favoritism, likely driving the observed increase in effect size.[32] Taken together, Table 4 lends strong support for the existence of substantial favoritism.

Tables 3 and 4 suggest the absence of birth region favoritism at the extensive margin but a strong presence of it at the intensive margin. This combined result may be rooted in the decision-making process within OFDA. As discussed in more detail in Section 6, US ambassadors have the authority to grant small amounts of aid on behalf of OFDA as an initial response to disasters. This type of decision is made quickly after disaster onset, when the full geographic spread of a disaster may not yet be fully understood. Hence, it may not leave much room for complex strategic considerations that would be reflected in regional favoritism. In cases where the ambassador's rapid-response assistance is deemed insufficient, more detailed impact assessment and coordination take place to determine further steps, creating substantial room for the formation of favoritism.

We next perform a series of placebo tests in Table 5 that exploit discontinuities of birth region status over time and the random timing of rapid-onset disasters to further ease endogeneity concerns. We reproduce columns 1 and 2 from Tables 3 and 4 with the addition of the placebo indicator.[33] Results confirm the absence of systematic favoritism

[32] The indicators we investigated are extent of clientelism in public spending, the quality of the local bureaucracy, and government accountability. A more detailed discussion of these indicators is provided in Section 6.

[33] Since this analysis exploits variation in the timing of disasters, we do not include year fixed effects to ensure sufficient power.

at the extensive margin. The placebo indicator is not only positive and significant but also exceeds the birth region indicator in size in both specifications. In stark contrast to this, the placebo estimates in the aid amounts regressions are negative and insignificant, while the birth region coefficients themselves remain positive and highly significant. This is further evidence that birth region effects are attributed to the political power of affected areas, rather than being driven by unobserved inherent characteristics of birth regions.

Table 5. Placebo models

	(1) *Any funding*	(2) *Any funding*	(3) *Log funding*	(4) *Log funding*
Birth region	0.053***	0.024*	0.608***	0.480***
	(0.015)	(0.014)	(0.158)	(0.155)
Placebo	0.077***	0.063**	-0.073	-0.157
	(0.028)	(0.029)	(0.250)	(0.278)
Controls		X		X
Fixed effects				
Country	X	X	X	X
Disaster type		X		X
Bias-corrected p-value	n/a	n/a	0.0001	0.0002
Direct test (p-value)	n/a	n/a	0.0159	0.0373
Observations	6,161	6,161	836	836
R^2	0.068	0.115	0.151	0.227

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses. The table replicates columns 1 and 2 from Tables 3 and 4 with the addition of the placebo indicator. The underlying test statistics for the bias-corrected p-values are calculated by subtracting the placebo coefficient from the birth region coefficient and dividing by the standard error of the birth region coefficient. The direct tests consider the Null hypothesis that the birth region and placebo coefficients are equal.

To further substantiate this point, we conduct two formal tests. First, we divide the difference between the birth region and placebo coefficients by the standard error of the birth region estimate in order to test whether the bias-adjusted birth region coefficient remains statistically significant. As shown by the bias-corrected p-values at the bottom of Table 5, this is clearly the case (with p-values < 1%). A potential problem with this approach is that the placebo estimates may suffer from a lack of power and only happen to be close to zero. We therefore conduct a second more conservative test, in which we directly test whether the birth region and placebo estimates are significantly different from each other. The results are reassuring. This more conservative test also yields statistically significant results (with p-values <5%). Therefore, the placebo analysis suggests that our results cannot be explained by characteristics inherent to potential birth regions.

Taken together, the previous analyses thus demonstrate that there is strong evidence in line with regional favoritism at the intensive margin while we do not find systematic evidence for the decision of whether or not to grant aid in the first place. Before discussing further extensions to the main regression models, we proceed with analyzing potential factors facilitating the observed relationship.

6. Do US-interests facilitate the home bias?

In this section we test whether the birth region-effect we have uncovered is actively supported by the United States or is exclusively the result of recipient country politics, in tandem with the absence of sufficient safeguards to prevent such favoritism. To discern how regional favoritism can enter the decision process on humanitarian aid amounts, it is useful to first review how the OFDA response to disasters unfolds. As mentioned earlier, the disaster response usually begins with a US diplomat, either a US Ambassador, Chief of Mission or US Assistant Secretary of State, responding to an assistance request from the recipient country's government.[34] This occurs when the disaster magnitude is declared to exceed the response capacity of affected countries. Afterwards, usually within 24 hours, the US diplomat can allocate a limited amount of up to US$ 50,000 (OFDA, 2010; Margesson, 2013, Kevlihan et al., 2014).[35]

OFDA officials coordinate with the government of the affected countries to determine whether and how much additional aid should be granted. Importantly, while the level of coordination can vary, the governments of affected countries are usually involved in the needs assessments by OFDA, which serve as a basis for determining additional aid amounts. The involvement of recipient countries can be either passive, by providing information on the disaster damage, or active, by participating in joint assessments with

[34] Alternatively, recipient countries can also accept an offer from US representatives.
[35] Before 2003, the limited amount was US$ 25,000 (Kevlihan et al., 2014).

OFDA teams. The OFDA teams deployed to the affected areas to carry out these assessments vary in size. For instance, a five-person team was sent to affected areas by typhoon Megi in the Philippines in 2010. The team's objective was to identify humanitarian needs together with officials of the Government of the Philippines, among others. The assessment was later used as a basis to allocate additional funds amounting to US$ 1.1 million (OFDA, 2011). For the case of large-scale disasters, bigger elite missions of humanitarian experts and technical advisors are deployed to the affected areas.[36] For example, the team for Hurricane Matthew affecting Haiti, Jamaica and the Bahamas in 2016 surpassed 70 members at its peak. Moreover, OFDA can grant additional aid without the deployment of teams to the affected areas, in which case information provided by local governments further gains in importance (OFDA, 2008-2017; Margesson, 2013, Kevlihan et al., 2014).

The involvement of the government in damage assessments, as well as the difficulties in verifying all governmental information, could enable country leaders to favor disasters hitting their birth regions in multiple ways. First, assessments might become more accurate for such disasters, improving their quality and increasing the likelihood of higher aid amounts, while no such care might be taken when non-birth regions are hit. Second, both the number of casualties and physical damage could be intentionally magnified for disasters hitting birth regions. Third, if non-birth regions are more likely to be politically misaligned with the country leader, disasters affecting those regions could be intentionally underplayed, or governments could hinder the entry of humanitarian aid to the country.[37]

As our setting puts the relationship between the population in disaster-affected areas and the country leader at the center of the analysis, it is natural to argue that leader's interests are at work. Following this logic, leaders might favor their birth regions for two reasons. They might simply derive utility from supporting a community they identify with, or attempt to ensure electoral and political support from their stronghold (Hodler and Raschky, 2014;

[36] In the US fiscal year of 2017, a record of 6 out of 53 disasters with OFDA funding required such missions, referred to as disaster assistance response teams (DARTs, see OFDA, 2017).
[37] For instance, the government of Burma was criticized for blocking and delaying the entry of humanitarian aid for the damages caused by cyclone Nargis in 2008 (Martin and Margesson, 2008; OFDA, 2008).

Carozzi and Repetto, 2016; Fiva and Halse, 2016; Do et al., 2017; Anaxagorou et al., 2019; Dreher et al., 2019).

Nevertheless, the political and economic interests of the United States might also be at play and facilitate additional funding for disasters affecting the birth region of leaders. In this section, we focus on two dimensions that we expect to increase the US government's stakes in a recipient country. The first is geopolitical alignment, which is often proxied with a country's voting behavior in the United Nations General Assembly (e.g., Fuchs and Klann, 2013). Using this proxy, Faye and Niehaus (2012) show that the political interests of donor governments distort the allocation of aid towards their allies in election years, with the aim to help such allies stay in power.[38] Requests from leaders aligned with the United States might then be more likely to be approved. In order to test whether the United States selectively allocates its humanitarian aid towards its allies, we interact our birth region-indicator with a (lagged) measure for the share of votes in which the disaster-affected countries were in agreement with the United States in the UNGA.[39]

The second dimension we focus on is a recipient country's commercial relations to the United States. A substantial literature explores how trade can be used to punish or reward countries (Berger et al., 2013; Fuchs and Klann, 2013), potentially with the aim to harm or support incumbent governments. We capture economic ties by using dyadic trade data from the Correlates of War project (Barbieri et al., 2009; Barbieri and Keshk, 2016) and calculate the sum of (lagged) US imports from and exports to disaster-affected countries both as shares of US GDP and in absolute terms. Again, to the extent that the US government grants humanitarian aid with the aim to support the incumbent of the recipient country in mind, more aid should be granted to birth regions if the recipient's trade ties with the US are stronger.

[38] Also see Rommel and Schaudt (2017).

[39] We take UN voting data from Voeten (2013), relying on the fraction of votes for which the United States was in agreement with the respective recipient country (counting abstentions as half-agreement).

Table 6. Birth region effect and US interests

	(1) *Log funding*	(2) *Log funding*	(3) *Log funding*
Birth region	0.220	0.419**	0.424**
	(0.364)	(0.171)	(0.168)
Birth region X UNGA overlap	0.516		
	(0.988)		
Birth region X trade/GDP		-1.059	
		(0.690)	
Birth region X trade (absolute)			-0.009
			(0.005)
Controls	X	X	X
Fixed effects			
Country	X	X	X
Disaster type	X	X	X
Year	X	X	X
Observations	806	823	823
R^2	0.339	0.335	0.335

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses. The dependent variable is the disaster-specific log funding in 2017 US dollars, conditioning on having received any funding. The variable birth region takes the value of one for disasters that hit the birth region of the country leader and zero otherwise. Absolute trade values are scaled to 2017 Billion US dollars. The main effects of the interacted variables are included in the regressions.

We show the results in Table 6. As can be seen, neither political nor commercial motives seem to be at play. Column 1 shows no evidence to support the idea of political interests exacerbating or ameliorating regional favoritism. According to columns 2 and 3, trade with the United States does not significantly affect the degree of favoritism in humanitarian aid, suggesting that US economic interests do not influence the observed effect. Overall, the results thus show no evidence in support of the hypothesis that the United States uses its humanitarian aid to facility requests from closer allies over those from more distant countries, in terms of geo-political and commercial relations.

In order to further test the potential role of the United States in the birth region-effect, we focus on a number of variables that we expect to affect how the US evaluates appeals. According to Eisensee and Strömberg (2007), the US government is particularly keen to support countries hit by disasters when they receive more media attention in the US, arguably because it pleases their own support base. We thus focus on US media attention to natural disasters, exploiting information stored in the Vanderbilt Television News Archive (n.d.), and create a binary indicator capturing whether a disaster was featured at least once during the evening news of the ABC news network.[40] When media attention is larger the US government will find it harder to support its allies. At the same time, media attention might increase US scrutiny for favoritism-based requests from the recipient, which would also reduce the home bias-effect.

We similarly expect the US government to be more skeptical of politically charged requests for help in countries with pronounced clientelism, low bureaucratic quality, and weak governance, as these are arguably those environments where the abuse of funds is most likely. We also test whether the US is more attentive at (recipient country) election time, as it is in such years that recipient country leaders might be most keen to misrepresent need and channel additional funds to their birth region (Anaxagorou, et al. 2019; Dreher et al., 2019).

For this exercise, we use a continuous index from the Variety of Democracy (V-Dem) project, in which higher scores stand for a lower degree of clientelism in government spending (i.e., a larger fraction of social and infrastructure expenditures are public goods rather than favoring particularistic interests). This indicator is based on country expert assessments and covers all countries and years in our sample (Coppedge et al., 2018). Second, we make use of two measures for quality of bureaucracy and democratic accountability obtained from the International Country Risk Guide/ICRG (ICRG, 2013). The former captures the institutional strength and autonomy of local bureaucracies on a scale from 0 to 4, with higher values indicating that the bureaucracy is able to govern without drastic policy changes or service interruptions (for instance, thanks to established staff recruiting systems and administrative procedures). The latter measure ranks countries on a scale from 0 to 6 taking into consideration the degree of political competition as well as checks and balances. Again, higher values indicate higher quality. Unlike the V-Dem data, the ICRG measures are not based on expert judgement but follow

[40] Vanderbilt Television News Archive only began recording on August 5th, 1968, leading to a small loss in the number of observations. We focus on ABC, as other major news networks such as CNN or Fox News started operating at a later date and would hence be unavailable for a large number of disasters. Matching of news reports and disasters is done on the basis of disaster dates as well as news content summaries reported in the Vanderbilt Television News Archive.

predetermined coding rules (see ICRG, 2013 for details).[41] Finally, we make use of election data from Cruz et al. (2018) to estimate our models interacted with election indicators. We construct election indicators that take the value of one if an executive, legislative or any of the two type of elections took place within five months after the disaster month.[42]

Table 7. Birth region effect and factors influencing US evaluation of appeals

	(1) *Log funding*	(2) *Log funding*	(3) *Log funding*	(4) *Log funding*	(5) *Log funding*	(6) *Log funding*	(7) *Log funding*
Birth region	0.357**	0.412***	1.402***	1.204**	0.350**	0.390**	0.365**
	(0.159)	(0.146)	(0.290)	(0.532)	(0.149)	(0.147)	(0.148)
Birth region X Media	-0.121						
	(0.256)						
Birth region X Particularistic		-0.261*					
		(0.144)					
Birth region X Bureaucracy			-0.619***				
			(0.161)				
Birth region X Accountability				-0.215*			
				(0.118)			
Birth region X Ex. elections					0.668		
					(0.610)		
Birth region X Leg. elections						-0.288	
						(0.451)	
Birth region X Elections							0.146
							(0.475)
Controls	X	X	X	X	X	X	X
Fixed effects							
Country	X	X	X	X	X	X	X
Disaster type	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X
Observations	761	836	551	551	835	835	835
R^2	0.402	0.348	0.389	0.378	0.345	0.344	0.344

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses. The dependent variable is the disaster-specific log funding in 2017 US dollars, conditioning on having received any funding. The variable birth region takes the value of one for disasters that hit the birth region of the country leader and zero otherwise. The main effects of the interacted variables are included in the regressions.

[41] A drawback of the ICRG data is that they are only available to us for the sub-period 1985 to 2012 and fully unavailable for Afghanistan, Nepal and Tajikistan.

[42] Results are unchanged when we focus on 11 months after the disaster occurs.

Table 7 reports the additional results. According to column 1, US media attention does not significantly moderate the degree of regional favoritism. As shown in column 2, countries with a higher fraction of public relative to particularistic spending behavior exhibit less regional favoritism. Moreover, both a better quality of the local bureaucracy (column 3) as well as higher government accountability (column 4) are significantly associated with less regional favoritism. Columns 5 to 7 show that none of the interactions with election indicators is statistically significant. Taken together, the evidence is thus not consistent with a storyline in which the United States carefully polices its funds with the goal to prevent potential abuse for domestic political purposes. Quite the contrary, it seems that recipient country leaders prone to clientelism and with weak bureaucracy and governance channel higher amounts of aid to disasters hitting their birth regions.

Our results also speak to potential motives of recipient country leaders. Conceptually, altruistic, electoral or political reasons more broadly might drive the home bias that we detect. A detailed test of these different channels is beyond the means of this paper. However, our results show that short-term electoral motives do not seem to dominate, as favoritism should then become stronger in the run-up for national elections in disaster-affected countries. As we do not find evidence for electoral motives behind the observed birth region effect, favoritism is more likely to reflect leaders' intrinsic desire to assist their own birth regions.[43] We find the home bias to be stronger rather than weaker in countries with stronger clientelism and weaker bureaucracy as well as governance, which are arguably environments that give domestic political leaders more leeway in pursuing their own interests. To the contrary, we have no reason to assume that the US government would want to channel more aid to the birth regions of the leaders of such countries. In summary, it thus seems that OFDA either lacks the motive or the means to prevent recipient governments from favoring birth regions, but does not actively support the misallocation of funds.

[43] This interpretation matches evidence from Vietnam according to which politicians channel public resources to their hometowns due to social preferences rather than expected political gains (Do et al., 2017).

7. Extensions

Total US disaster assistance

As previously discussed in Section 2, OFDA is the chief agency for US disaster assistance but there are other USAID offices (e.g., Office of Food for Peace) or ministries that also contribute humanitarian aid for certain disasters. Given that OFDA provides approximate numbers for these contributions for the 1964 to 2004 sub-period, we are able to formally test whether the previously obtained results are representative for the United States at large, or pertain to OFDA only.[44] In Table 8, we replicate columns 1 to 3 of Table 4, using total US government contributions as reported by OFDA. To facilitate comparison, we also show regressions with OFDA funding restricted to the same sub-period. While the results for OFDA remain similar to those obtained with the full sample, point estimates increase in magnitude when we include all contributions, suggesting that favoritism might become more salient when multiple US agencies are involved.[45] Given these estimates, we interpret the key findings of this study to be representative for US humanitarian aid at large.

Table 8. Total US government contributions, Log funding

	(1) *All*	(2) *All*	(3) *All*	(4) *OFDA*	(5) *OFDA*	(6) *OFDA*
Birth region	0.755***	0.758***	0.713***	0.459***	0.489***	0.419**
	(0.198)	(0.230)	(0.243)	(0.141)	(0.164)	(0.170)
Controls (local area characteristics)		X	X		X	X
Fixed effects						
Country	X	X	X	X	X	X
Disaster type		X	X		X	X
Year			X			X
Observations	633	633	633	587	587	587
R^2	0.171	0.241	0.318	0.149	0.235	0.313

Notes: ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses. The table replicates columns 1 to 3 from Table 4 using all US funding in columns 1 to 3 and OFDA only in columns 4 to 6.

[44] Due to the shorter time period, within-country variation is reduced to the extent that we refrain from estimating disaster-area fixed effects models using total US government contributions.

[45] A potential reason for this could be that procedures become more complex, making it easier for a recipient country's political leaders to favor their regions.

Ethnic favoritism

A potential explanation for our main results relates to the overlap of birth regions with ethnic homelands of country leaders. As such, the estimated birth region effects might be driven by ethnicity rather than birth region. To test this possibility, we exploit variation in the ethnic identity of the population in disaster-affected areas and generate an alternative measure of favoritism based on the ethnic identity of the political leader.[46]

To determine the geographic spread of ethnic settlement patterns, the political-economy literature on ethnicity heavily relies on ethno-linguistic or expert-based maps, such as *GREG* (Weidmann et al., 2010), Ethnologue (Gordon, 2005), and *GeoEPR* (Wucherpfennig et al., 2011).[47] In addition to being based on potentially outdated, one-dimensional, or incomplete information, these approaches come with the major disadvantage of failing to capture the nuanced realities of actual settlement patterns.[48] Therefore, this paper follows a novel approach of using IPUMS census data and DHS data.[49] IPUMS-International provides microdata for 98 countries. It currently covers more than one billion people in 443 censuses. The data are consistent across countries and over time and represent the largest available archive of publicly available census data (MEASURES DHS, 2017; Minnesota Population Center, 2017, 2019).

[46] For the identification of leader ethnicities, we augment the Archigos database with leader ethnicity information acquired from Fearon et al. (2007), Parks (2014) and through online search. We provide an overview of leader ethnicities in Table A1.

[47] See, for instance, Alesina et al. (2016), Guariso and Rogall (2017), and Anaxagorou et al. (2019).

[48] For instance, according to Weidmann et al. (2010), details on sources, definitions, and coding conventions of the *Atlas Narodov Mira* which serves as a base for GREG are not documented. Weidmann et al. (2010) however infer the coding criteria by comparing sub-samples with data on ethnicities from other sources. They conclude that the distinction between groups within countries is mainly based on language. This ignores important differences between ethnic groups. For example, the Sunni-Shi'ite division in Iraq is ignored, as is those between the Hutus and Tutsis in Rwanda, even though these are among the most important cleavages in their countries (Wucherpfennig et al., 2011).

[49] Weidmann et al. (2010: 492) mention the possibility to "infer the location of ethnic groups from survey or census data." According to Weidmann et al. (2010: 492) "providing spatially referenced census data for a larger set of cases is not possible." We disagree and do exactly this (see Gershman and Rivera, 2018, for a similar approach to coding the ethno*linguistic* composition of sub-national regions in Sub-Saharan Africa).

Table 9. Birth region and ethnic homelands

	(1) *Log funding*	(2) *Log funding*	(3) *Log funding*	(4) *Log funding*	(5) *Log funding*	(6) *Log funding*
Birth region	0.492***	0.410**	0.362*	0.539***	0.431***	0.373**
	(0.159)	(0.161)	(0.180)	(0.149)	(0.150)	(0.163)
Ethnic homeland	0.117	0.085	0.069			
	(0.225)	(0.244)	(0.256)			
Ethnic share				-0.046	0.062	0.238
				(0.303)	(0.341)	(0.387)
Controls		X	X		X	X
Fixed effects						
Country	X	X	X	X	X	X
Disaster type		X	X		X	X
Year			X			X
Observations	673	673	673	673	673	673
R^2	0.137	0.224	0.339	0.136	0.223	0.339

Notes: Table replicates columns 1 to 3 from Table 4. ***, **, * denote statistical significance at the 1, 5 and 10% level respectively, with clustered standard errors in parentheses.

We exploit the precise estimates provided by the census data to define ADM1-level ethnic homelands satisfying at least one of the three following requirements: (i) the ethnic share of the region's population is of at least 90%, (ii) the region is among the top decile of ethnic shares, (iii) the ethnic share of the region's population is between the highest ethnic share observed in other regions and 10% below. Moreover, in cases where (ii) holds but the ethnic share of the region's population is less than 50% of the highest ethnic share observed in other regions, we do not consider the region an ethnic homeland.[50] Once all ethnic homelands are determined, we match them to the ethnicities of country leaders. We then code a binary indicator that equals one if a disaster hit the ethnic homeland of the political leader.[51] To make sure that our results do not depend on specific choices made when defining ethnic homelands, we further create a continuous measure capturing

[50] Rule (i) describes ethnic majority regions. Rule (ii) is useful to identify homelands of ethnic minorities who never reach a population share of 90%. We introduce rule (iii) as it may be the case that regions that are covered by rule (ii) do not necessarily exhibit a substantially higher population share than those closely below this cutoff. It is further possible that regions covered by rule (ii) comprise both areas with very high and very low population shares if an ethnicity is mainly centered in one or two regions of a country. The final requirement therefore imposes a restriction on the allowed divergence from the most important region from the perspective of the ethnicity.

[51] Note that given the definition of ethnic homelands applied in this paper, it is possible that a leader has multiple ethnic homelands. In these cases, the binary indicator equals one if a disaster hit at least one of these homelands.

the share of the population in disaster-affected areas belonging to the same ethnicity as the political leader ("ethnic share").[52]

In Table 9, we replicate columns 1 to 3 of Table 4 adding either the binary ethnic homeland indicator or the ethnic share. While the sample is reduced to 37 countries for which ethnic data are available, the birth region effect remains both economically and statistically significant in all specifications. By contrast, the influence of both ethnic homelands and ethnic share never reach statistical significance. Consequently, ethnic power relations do not seem to explain the observed birth region effect.[53]

8. Conclusion

With poor response capacities and vulnerable economies, low- and middle-income countries are particularly exposed to the impacts of natural disasters. Over the 1964 to 2017 period, each of such calamities in our sample resulted in the death of 360 people, on average. In addition to high casualty numbers, natural disasters can potentially lead to a range of adverse outcomes such as weaker economic growth (Felbermayr and Gröschl, 2014) or human capital deficits of future adult generations (Caruso, 2017; Dinkelman, 2017). International humanitarian aid therefore potentially fulfills a crucial role by providing affected countries with much-needed relief goods, financial means, organizational support and expertise, and thereby reducing the macro- and micro-costs of natural disasters.

However, in order to ensure that aid is granted to those who are most in need, it is essential to understand political and economic rationales that could distort the allocation

[52] Given that the geographic distribution of disaster victims is not reported, disasters affecting multiple regions are handled by calculating an area-weighted average of the ethnic composition of all affected ADM1 regions (or ADM2 areas if available).

[53] As Ahlerup and Isaksson (2015) point out, ethnic and regional favoritism are conceptually distinct from each other. Our results match those of Dreher et al. (2019) for Chinese development finance. However, unlike Dreher et al., who analyze ethnicity effects at the level of traditionally defined ethnic homelands based on *GREG* data, we are able to analyze both birth region and ethnicity effects at the level of ADM1 regions for aid flows directed to the same regions, ruling out the possibility that the differential effects are driven by varying geographic coverage. This feature of our data further allows us to estimate interaction effects between ethnic homelands and birth regions. These are, however, statistically insignificant in all specifications (results available on request).

of aid and thus reduce the effectiveness of disaster relief.[54] Our study contributes to the literature by taking a unique and new perspective that puts a *domestic political factor within a large number of recipient countries* at its center. In the first sub-national analysis of its kind, we have uncovered the importance of regional favoritism for the allocation of disaster aid. According to our results, disasters hitting birth regions of political leaders receive substantially higher amounts of humanitarian aid than other comparable disasters. This result is robust to netting out effects of local area characteristics and disaster magnitude.

Moreover, both disaster-area fixed effects and placebo models indicate that the effect is not related to the inherent unobserved characteristics of the affected areas, but attributed to the importance they hold when being hit by disasters. Furthermore, we do not find evidence that ethnic power relations govern the observed relationship. Nor is there evidence that the United States government actively promotes the birth region effect in order to please political leaders of countries with close political or commercial ties. To the contrary, regional favoritism seems to be weaker in countries where social and infrastructure spending tends to follow public interests, where bureaucracies are more able to resist political influence, and where governments are held accountable by reliable institutions and political competition, suggesting that the birth-region effect is driven by recipient country politics, facilitated by US policies that seem to neglect the internal political dynamics in the countries receiving its aid.

Our results have important policy implications. First, we identify the existence of favoritism in an extreme scenario of humanitarian need. While similar forms of favoritism have previously been observed in the contexts of Chinese development aid (Dreher et al., 2019) and economic growth (Hodler and Raschky, 2014), the fact that discriminatory politics are applied even when human lives are directly at stake is alarming. Our analysis thus calls for further research on this topic and the exploration of realistic possibilities of engaging in corrective action. In particular, even though we do not find evidence that the observed effects are driven by donor's political and economic interests, it is imperative to revise

[54] See Dreher et al. (2018) on the importance of political motives for the effectiveness of aid and De Mel et al. (2012) for an example on the effectiveness of disaster relief in the context of enterprise recovery.

established processes related to disaster damage assessment and aid allocation in order to reduce the scope for manipulation by recipient country leaders.

This policy implication should be prioritized for two reasons. First, given that the results appear to be driven by recipient countries, it is likely that aid from other donor countries is similarly affected to the extent that these donors apply decision-making processes comparable to those of the United States. Second, as with accelerating climate change, natural disasters are projected to significantly increase in both frequency and intensity (IPCC, 2018), the relevance of effective humanitarian aid will likely increase in the near future.

A further policy implication of our findings relates to the long-term consequences of natural disasters. As leaders' birth regions tend to already be among the richer regions of their country (Hodler and Raschky, 2014; Dreher et al., 2019), regional favoritism in humanitarian aid could further exacerbate within-country inequalities. This is especially problematic given the potential of natural disasters to cause adverse long-run social and economic consequences. In order to ensure that disaster relief activities do not counteract international efforts to reduce inequality within poor countries, donors need to increase their efforts to incorporate concerns of regional equity in their aid allocation decisions.

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Appendix

Table A1. Leader list

Country	Leader	Start date	End date	Birth region	ADM1 reference point	Ethnicity	Census/ survey year(s)
Afghanistan	Mohammad Daud Khan	07.09.1953	10.03.1963	Kabul	Province	Pashtun	2010
Afghanistan	Mohammad Yusuf Khan	10.03.1963	02.11.1965	Kabul	Province	Pashtun	2010
Afghanistan	Mohammad Hashim Maiwandwal	02.11.1965	11.10.1967	Kabul	Province	n/a	2010
Afghanistan	Abdullah Yaqta	11.10.1967	01.11.1967	n/a	Province	n/a	2010
Afghanistan	Mohammad Nur Ahmad Etemadi	01.11.1967	09.06.1971	n/a	Province	n/a	2010
Afghanistan	Abdul Zahir	09.06.1971	06.12.1972	n/a	Province	Pashtun	2010
Afghanistan	Mohammad Musa Shafiq	12.12.1972	17.07.1973	n/a	Province	n/a	2010
Afghanistan	Mohammad Daud Khan	17.07.1973	27.04.1978	Kabul	Province	Pashtun	2010
Afghanistan	Nur Muhammad Taraki	30.04.1978	27.03.1979	Ghazni	Province	Pashtun	2010
Afghanistan	Hafizullah Amin	27.03.1979	27.12.1979	Kabul	Province	Pashtun	2010
Afghanistan	Babrak Karmal	27.12.1979	04.05.1986	Kabul	Province	Pashtun	2010
Afghanistan	Najibullah Ahmadzai	04.05.1986	16.04.1992	Paktya	Province	Pashtun	2010
Afghanistan	Sibghatullah Mojaddedi	28.04.1992	28.06.1992	Kabul[a]	Province	Pashtun	2010
Afghanistan	Burhanuddin Rabbani	28.06.1992	27.09.1996	Badakhshan	Province	Tajik	2010
Afghanistan	Mullah Mohammed Omar	27.09.1996	13.11.2001	Kandahar	Province	Pashtun	2010
Afghanistan	Hamid Karzai	22.12.2001	29.09.2014	Kandahar	Province	Pashtun	2010
Afghanistan	Ashraf Ghani Ahmadzai	29.09.2014	in office[d]	Logar	Province	Pashtun	2010
Angola	Agostinho Neto	11.11.1975	10.09.1979	Bengo	Province (2010)		
Angola	José Eduardo dos Santos	10.09.1979	26.09.2017	Luanda	Province (2010)		
Angola	João Lourenço[e]	26.09.2017	in office[d]	Benguela	Province (2010)		
Argentina	Arturo Umberto Illia Francesconi	12.10.1963	28.06.1966	Buenos Aires	Province		
Argentina	Juan Carlos Onganía Carballo	28.06.1966	08.06.1970	Buenos Aires	Province		
Argentina	Alejandro Agustín Lanusse	08.06.1970	18.06.1970	Buenos Aires (City)	Province		
Argentina	Roberto Marcelo Levingston	18.06.1970	22.03.1971	San Luis	Province		
Argentina	Alejandro Agustín Lanusse	25.03.1971	25.05.1973	Buenos Aires (City)	Province		
Argentina	Héctor José Cámpora	25.05.1973	13.07.1973	Buenos Aires	Province		
Argentina	Raúl Alberto Lastiri	13.07.1973	12.10.1973	Buenos Aires (City)	Province		
Argentina	Juan Domingo Perón	12.10.1973	01.07.1974	Buenos Aires	Province		
Argentina	Isabel Perón	01.07.1974	29.03.1976	La Rioja	Province		
Argentina	Jorge Rafael Videla	29.03.1976	29.03.1981	Buenos Aires	Province		
Argentina	Roberto Eduardo Viola	29.03.1981	20.11.1981	Buenos Aires (City)	Province		
Argentina	Horacio Tomás Liendo	20.11.1981	11.12.1981	Córdoba	Province		
Argentina	Leopoldo Galtieri	12.12.1981	17.06.1982	Buenos Aires	Province		
Argentina	Alfredo Oscar Saint-Jean	18.06.1982	01.07.1982	n/a	Province		
Argentina	Reynaldo Bignone	01.07.1982	10.12.1983	Buenos Aires	Province		
Argentina	Raúl Ricardo Alfonsín	10.12.1983	08.07.1989	Buenos Aires	Province		
Argentina	Carlos Saúl Menem	08.07.1989	10.12.1999	La Rioja	Province		
Argentina	Fernando de la Rúa	10.12.1999	21.12.2001	Córdoba	Province		
Argentina	Federico Ramón Puerta	21.12.2001	23.12.2001	Misiones	Province		
Argentina	Adolfo Rodríguez Saá	23.12.2001	01.01.2002	San Luis	Province		
Argentina	Eduardo Alberto Duhalde	02.01.2002	25.05.2003	Buenos Aires	Province		
Argentina	Néstor Carlos Kirchner	25.05.2003	10.12.2007	Santa Cruz	Province		
Argentina	Cristina Fernández de Kirchner	10.12.2007	10.12.2015	Buenos Aires	Province		
Argentina	Mauricio Macri	10.12.2015	in office[d]	Buenos Aires	Province		
Bangladesh	Syed Nazrul Islam	11.04.1971	10.01.1972	Dhaka	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Sheikh Mujibur Rahman	13.01.1972	15.08.1975	Dhaka	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Khondaker Mostaq Ahmad	15.08.1975	06.11.1975	Chittagong	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Ziaur Rahman	06.11.1975	30.05.1981	Rajshahi	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Abdus Sattar	30.05.1981	20.03.1982	India*	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Hussain Muhammad Ershad	27.03.1982	06.12.1990	Rangpur[b]	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Shahabuddin Ahmed	06.12.1990	20.03.1991	Mymensingh	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Khaleda Zia	20.03.1991	30.03.1996	Rangpur	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Muhammad Habibur Rahman	30.03.1996	23.06.1996	India*	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Sheikh Hasina Wazed	23.06.1996	15.07.2001	Dhaka	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Latifur Rahman	15.07.2001	10.10.2001	Khulna	Division (2014)	n/a	91,01,11
Bangladesh	Khaleda Zia	10.10.2001	29.10.2006	Rangpur	Division (2014)	Bengali Muslim	91,01,11
Bangladesh	Iajuddin Ahmed	29.10.2006	12.01.2007	Dhaka	Division (2014)	n/a	91,01,11
Bangladesh	Fakhruddin Ahmed	12.01.2007	06.01.2009	Dhaka	Division (2014)	n/a	91,01,11
Bangladesh	Sheikh Hasina Wazed	06.01.2009	in office[d]	Dhaka	Division (2014)	Bengali Muslim	91,01,11
Bolivia	Ángel Víctor Paz Estenssoro	06.08.1960	04.11.1964	Tarija	Department	White/Mestizo	2001
Bolivia	René Barrientos Ortuño	06.11.1964	05.01.1966	Cochabamba	Department	White/Mestizo	2001
Bolivia	Alfredo Ovando Candía	05.01.1966	06.08.1966	Pando	Department	White/Mestizo	2001
Bolivia	René Barrientos Ortuño	06.08.1966	27.04.1969	Cochabamba	Department	White/Mestizo	2001
Bolivia	Luis Adolfo Siles Salinas	27.04.1969	26.09.1969	La Paz	Department	White/Mestizo	2001
Bolivia	Alfredo Ovando Candía	26.09.1969	06.10.1970	Pando	Department	White/Mestizo	2001
Bolivia	Juan José Torres González	07.10.1970	22.08.1971	Cochabamba	Department	White/Mestizo	2001
Bolivia	Hugo Banzer Suárez	22.08.1971	21.07.1978	Santa Cruz	Department	White/Mestizo	2001
Bolivia	Juan Pereda Asbún	21.07.1978	24.11.1978	La Paz	Department	White/Mestizo	2001
Bolivia	David Padilla Arancibia	24.11.1978	08.08.1979	n/a	Department	White/Mestizo	2001
Bolivia	Wálter Guevara Arze	08.08.1979	01.11.1979	Cochabamba	Department	White/Mestizo	2001
Bolivia	Alberto Natusch Busch	01.11.1979	16.11.1979	n/a	Department	White/Mestizo	2001
Bolivia	Lidia Gueiler Tejada	16.11.1979	17.07.1980	Cochabamba	Department	White/Mestizo	2001
Bolivia	Luis García Meza Tejada	18.07.1980	04.08.1981	La Paz	Department	White/Mestizo	2001
Bolivia	Celso Torrelio Villa	05.08.1981	19.07.1982	Chuquisaca	Department	White/Mestizo	2001

Bolivia	Guido Vildoso Calderón	21.07.1982	10.10.1982	n/a	Department	White/Mestizo	2001
Bolivia	Hernán Siles Zuazo	10.10.1982	06.08.1985	La Paz	Department	White/Mestizo	2001
Bolivia	Ángel Víctor Paz Estenssoro	06.08.1985	06.08.1989	Tarija	Department	White/Mestizo	2001
Bolivia	Jaime Paz Zamora	06.08.1989	06.08.1993	Cochabamba	Department	White/Mestizo	2001
Bolivia	Gonzalo Sánchez de Lozada	06.08.1993	06.08.1997	La Paz	Department	White/Mestizo	2001
Bolivia	Hugo Banzer Suárez	06.08.1997	07.08.2001	Santa Cruz	Department	White/Mestizo	2001
Bolivia	Jorge Quiroga Ramírez	07.08.2001	06.08.2002	Cochabamba	Department	White/Mestizo	2001
Bolivia	Gonzalo Sánchez de Lozada	08.08.2002	17.10.2003	La Paz	Department	White/Mestizo	2001
Bolivia	Carlos Diego Mesa Gisbert	17.10.2003	09.06.2005	La Paz	Department	White/Mestizo	2001
Bolivia	Eduardo Rodríguez Veltzé	09.06.2005	22.01.2006	Cochabamba	Department	White/Mestizo	2001
Bolivia	Juan Evo Morales Ayma	22.01.2006	in office[d]	Oruro	Department	Aymara	2001
Brazil	João Belchior Marques Goulart	07.09.1961	02.04.1964	Rio Grande do Sul	State	White	2000
Brazil	Pascoal Ranieri Mazzilli	02.04.1964	15.04.1964	São Paulo	State	White	2000
Brazil	Humberto Castelo Branco	15.04.1964	15.03.1967	Ceará	State	White	2000
Brazil	Artur da Costa e Silva	15.03.1967	01.09.1969	Rio Grande do Sul	State	White	2000
Brazil	Military Junta	01.09.1969	25.10.1969	n/a	State	n/a	2000
Brazil	Emílio Garrastazu Médici	25.10.1969	15.03.1974	Rio Grande do Sul	State	White	2000
Brazil	Ernesto Beckmann Geisel	15.03.1974	15.03.1979	Rio Grande do Sul	State	White	2000
Brazil	João Figueiredo	15.03.1979	21.03.1985	Rio de Janeiro	State	White	2000
Brazil	José Sarney de Araújo Costa	21.03.1985	15.03.1990	Maranhão	State	White	2000
Brazil	Fernando Collor de Mello	15.03.1990	02.10.1992	Rio de Janeiro	State	White	2000
Brazil	Itamar Franco	02.10.1992	31.12.1994	Minas Gerais[b]	State	White	2000
Brazil	Fernando Henrique Cardoso	01.01.1995	01.01.2003	Rio de Janeiro	State	White	2000
Brazil	Luiz Inácio Lula da Silva	01.01.2003	01.01.2011	Pernambuco	State	White	2000
Brazil	Dilma Vana Rousseff	01.01.2011	31.08.2016	Minas Gerais	State	White	2000
Brazil	Michel Temer[e]	31.08.2016	in office[d]	São Paulo	State	White	2000
Chile	Jorge Alessandri Rodríguez	03.11.1958	03.11.1964	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Eduardo Frei Montalva	03.11.1964	03.11.1970	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Salvador Allende	04.11.1970	11.09.1973	Valparaíso	Region (2016)	White/Mestizo	92,00
Chile	Augusto Pinochet	11.09.1973	11.03.1990	Valparaíso	Region (2016)	White/Mestizo	92,00
Chile	Patricio Aylwin Azócar	11.03.1990	11.03.1994	Valparaíso	Region (2016)	White/Mestizo	92,00
Chile	Eduardo Frei Ruiz-Tagle	11.03.1994	11.03.2000	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Ricardo Froilán Lagos Escobar	12.03.2000	11.03.2006	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Michelle Bachelet	11.03.2006	11.03.2010	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Sebastián Piñera	11.03.2010	11.03.2014	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Michelle Bachelet	11.03.2014	11.03.2018	Santiago	Region (2016)	White/Mestizo	92,00
Chile	Sebastián Piñera	11.03.2018	in office[d]	Santiago	Region (2016)	White/Mestizo	92,00
China	Mao Zedong	01.10.1949	09.09.1976	Hunan	Province	Han	2000
China	Hua Guofeng	07.10.1976	10.09.1980	Shanxi	Province	Han	2000
China	Deng Xiaoping	10.09.1980	19.02.1997	Sichuan	Province	Han	2000
China	Jiang Zemin	19.02.1997	15.03.2003	Jiangsu	Province	Han	2000
China	Hu Jintao	15.03.2003	15.11.2012	Jiangsu	Province	Han	2000
China	Xi Jinping	15.11.2012	in office[d]	Shaanxi	Province	Han	2000
Colombia	Alberto Lleras Camargo	07.08.1958	07.08.1962	Capital District	Department	White/Mestizo	2005
Colombia	Guillermo León Valencia Muñoz	07.08.1962	07.08.1966	Cauca	Department	White/Mestizo	2005
Colombia	Carlos Alberto Lleras Restrepo	07.08.1966	07.08.1970	Capital District	Department	White/Mestizo	2005
Colombia	Misael Pastrana Borrero	07.08.1970	07.08.1974	Huila	Department	White/Mestizo	2005
Colombia	Alfonso López Michelsen	07.08.1974	07.08.1978	Capital District	Department	White/Mestizo	2005
Colombia	Julio César Turbay Ayala	07.08.1978	07.08.1982	Capital District	Department	Lebanese	2005
Colombia	Belisario Betancur Cuartas	07.08.1982	07.08.1986	Antioquia	Department	White/Mestizo	2005
Colombia	Virgilio Barco Vargas	07.08.1986	07.08.1990	N. de Santander	Department	White/Mestizo	2005
Colombia	César Augusto Gaviria Trujillo	07.08.1990	07.08.1994	Risaralda	Department	White/Mestizo	2005
Colombia	Ernesto Samper Pizano	07.08.1994	07.08.1998	Capital District	Department	White/Mestizo	2005
Colombia	Andrés Pastrana Arango	07.08.1998	07.08.2002	Capital District	Department	White/Mestizo	2005
Colombia	Álvaro Uribe Vélez	08.08.2002	07.08.2010	Antioquia	Department	White/Mestizo	2005
Colombia	Juan Manuel Santos Calderón	07.08.2010	in office[d]	Capital District	Department	White/Mestizo	2005
Costa Rica	Mario José Echandi Jiménez	08.05.1958	08.05.1962	San José	Province	White/Mestizo	2011
Costa Rica	Francisco Orlich Bolmarcich	08.05.1962	08.05.1966	Alajuela	Province	White/Mestizo	2011
Costa Rica	José Joaquín Trejos Fernández	08.05.1966	08.05.1970	San José	Province	White/Mestizo	2011
Costa Rica	José Figueres Ferrer	08.05.1970	08.05.1974	Alajuela	Province	White/Mestizo	2011
Costa Rica	Daniel Oduber Quirós	08.05.1974	08.05.1978	San José	Province	White/Mestizo	2011
Costa Rica	Rodrigo Carazo Odio	08.05.1978	08.05.1982	Cartago	Province	White/Mestizo	2011
Costa Rica	Luis Alberto Monge Álvarez	08.05.1982	08.05.1986	Alajuela	Province	White/Mestizo	2011
Costa Rica	Óscar Arias Sánchez	08.05.1986	08.05.1990	Heredia	Province	White/Mestizo	2011
Costa Rica	Rafael Ángel Calderón Fournier	08.05.1990	08.05.1994	Nicaragua*	Province	White/Mestizo	2011
Costa Rica	José María Figueres Olsen	08.05.1994	08.05.1998	San José	Province	White/Mestizo	2011
Costa Rica	M. Ángel Rodríguez Echeverría	08.05.1998	08.05.2002	San José	Province	White/Mestizo	2011
Costa Rica	Abel Pacheco de la Espriella	09.05.2002	08.05.2006	San José	Province	White/Mestizo	2011
Costa Rica	Óscar Arias Sánchez	08.05.2006	08.05.2010	Heredia	Province	White/Mestizo	2011
Costa Rica	Laura Chinchilla Miranda	08.05.2010	08.05.2014	San José	Province	White/Mestizo	2011
Costa Rica	Luis Guillermo Solís Rivera	08.05.2014	08.05.2018	San José	Province	White/Mestizo	2011
Costa Rica	Carlos Alvarado Quesada[e]	08.05.2018	in office[d]	San José	Province	White/Mestizo	2011
Cuba	Fidel Castro	02.01.1959	24.02.2008	Holguín	Province	White	2002
Cuba	Raúl Castro	24.02.2008	in office[d]	Holguín	Province	White	2002
DR Congo	Mobutu Sese Seko	14.09.1960	20.09.1960	Mongala	Province	UIN	2013
DR Congo	Joseph Kasa-Vubu	20.09.1960	25.11.1965	Kongo-Central	Province	Bakongo	2013
DR Congo	Mobutu Sese Seko	25.11.1965	16.05.1997	Mongala	Province	UIN	2013
DR Congo	Laurent Kabila	16.05.1997	16.01.2001	Tanganyika	Province	KKT	2013
DR Congo	Joseph Kabila	17.01.2001	in office[d]	Sud-Kivu	Province	KKT	2013
Dominican Rep.	Joseph Donald Reid Cabral	22.12.1963	25.04.1965	n/a	Province		
Dominican Rep.	José Rafael Molina Ureña	25.04.1965	27.04.1965	n/a	Province		
Dominican Rep.	Pedro Bartolomé Benoit	27.04.1965	07.05.1965	n/a	Province		
Dominican Rep.	Antonio Cosme Imbert Barrera	07.05.1965	30.08.1965	n/a	Province		
Dominican Rep.	Héctor García Godoy	03.09.1965	01.07.1966	Espaillat	Province		
Dominican Rep.	Joaquín Antonio Balaguer Ricardo	01.07.1966	01.07.1978	Santiago	Province		
Dominican Rep.	Antonio Guzmán Fernández	01.07.1978	04.07.1982	La Vega	Province		
Dominican Rep.	Jacobo Majluta Azar	04.07.1982	16.08.1982	n/a	Province		

Dominican Rep.	José Salvador Omar Jorge Blanco	16.08.1982	16.08.1986	Santiago	Province		
Dominican Rep.	Joaquín Antonio Balaguer Ricardo	16.08.1986	16.08.1996	Santiago	Province		
Dominican Rep.	Leonel Antonio Fernández Reyna	16.08.1996	16.08.2000	Distrito Nacional	Province		
Dominican Rep.	Rafael Hipólito Mejía Domínguez	17.08.2000	16.08.2004	Santiago	Province		
Dominican Rep.	Leonel Antonio Fernández Reyna	16.08.2004	16.08.2012	Distrito Nacional	Province		
Dominican Rep.	Danilo Medina Sánchez	16.08.2012	in office[d]	San Juan	Province		
Ecuador	Carlos Julio Arosemena Monroy	07.11.1961	11.07.1963	Guayas	Province	White/Mestizo	01,10
Ecuador	Ramón Castro Jijón	11.07.1963	29.03.1966	Esmeraldas	Province	White/Mestizo	01,10
Ecuador	Clemente Yerovi Indaburu	29.03.1966	16.11.1966	Catalonia	Province	White/Mestizo	01,10
Ecuador	Otto Arosemena Gómez	16.11.1966	01.09.1968	Guayas	Province	White/Mestizo	01,10
Ecuador	José María Velasco Ibarra	01.09.1968	15.02.1972	Pichincha	Province	White/Mestizo	01,10
Ecuador	Guillermo Rodríguez Lara	15.02.1972	11.01.1976	Cotopaxi	Province	White/Mestizo	01,10
Ecuador	Alfredo Ernesto Poveda Burbano	11.01.1976	10.08.1979	Tungurahua	Province	White/Mestizo	01,10
Ecuador	Jaime Roldós Aguilera	10.08.1979	24.05.1981	Guayas	Province	White/Mestizo	01,10
Ecuador	Luis Osvaldo Hurtado Larrea	24.05.1981	10.08.1984	Chimborazo	Province	White/Mestizo	01,10
Ecuador	León Febres Cordero	10.08.1984	10.08.1988	Guayas	Province	White/Mestizo	01,10
Ecuador	Rodrigo Borja Cevallos	10.08.1988	10.08.1992	Pichincha	Province	White/Mestizo	01,10
Ecuador	Sixto Durán Ballén	10.08.1992	10.08.1996	United States*	Province	White/Mestizo	01,10
Ecuador	Abdalá Jaime Bucaram Ortiz	10.08.1996	06.02.1997	Guayas	Province	Arab	01,10
Ecuador	Fabián Ernesto Alarcón Rivera	06.02.1997	09.02.1997	Pichincha	Province	White/Mestizo	01,10
Ecuador	Rosalía Arteaga Serrano	09.02.1997	11.02.1997	Azuay	Province	White/Mestizo	01,10
Ecuador	Fabián Ernesto Alarcón Rivera	11.02.1997	10.08.1998	Pichincha	Province	White/Mestizo	01,10
Ecuador	Jorge Jamil Mahuad Witt	10.08.1998	21.01.2000	Loja	Province	Arab	01,10
Ecuador	Gustavo Noboa	22.01.2000	15.01.2003	Guayas	Province	White/Mestizo	01,10
Ecuador	Lucio Edwin Gutiérrez Borbúa	15.01.2003	20.04.2005	Pichincha	Province	White/Mestizo	01,10
Ecuador	Luis Alfredo Palacio González	20.04.2005	15.01.2007	Guayas	Province	White/Mestizo	01,10
Ecuador	Rafael Vicente Correa Delgado	15.01.2007	24.05.2017	Guayas	Province	White/Mestizo	01,10
Ecuador	Lenín Boltaire Moreno Garcés[e]	24.05.2017	in office[d]	Orellana	Province	White/Mestizo	01,10
El Salvador	Julio Adalberto Rivera Carballo	01.07.1962	01.07.1967	La Paz	Department	White/Mestizo	2007
El Salvador	Fidel Sánchez Hernández	01.07.1967	01.07.1972	Morazán	Department	White/Mestizo	2007
El Salvador	Arturo Armando Molina	01.07.1972	01.07.1977	San Salvador	Department	White/Mestizo	2007
El Salvador	Carlos Humberto Romero	01.07.1977	15.10.1979	Chalatenango	Department	White/Mestizo	2007
El Salvador	Adolfo Arnaldo Majano Ramos	15.10.1979	07.12.1980	n/a	Department	White/Mestizo	2007
El Salvador	José Napoleón Duarte Fuentes	13.12.1980	02.05.1982	San Salvador	Department	White/Mestizo	2007
El Salvador	Álvaro Alfredo Magaña Borja	02.05.1982	01.06.1984	Ahuachapán	Department	White/Mestizo	2007
El Salvador	José Napoleón Duarte Fuentes	01.06.1984	01.06.1989	San Salvador	Department	White/Mestizo	2007
El Salvador	Alfredo Cristiani	01.06.1989	01.06.1994	San Salvador	Department	White/Mestizo	2007
El Salvador	Armando Calderón Sol	01.06.1994	01.06.1999	San Salvador	Department	White/Mestizo	2007
El Salvador	Francisco Flores Pérez	01.06.1999	01.06.2004	Santa Ana	Department	White/Mestizo	2007
El Salvador	Antonio Saca	01.06.2004	01.06.2009	Usulután	Department	White/Mestizo	2007
El Salvador	Carlos Mauricio Funes Cartagena	01.06.2009	01.06.2014	San Salvador	Department	White/Mestizo	2007
El Salvador	Salvador Sánchez Cerén	01.06.2014	in office[d]	La Libertad	Department	White/Mestizo	2007
Ethiopia	Haile Selassie I	05.05.1941	12.09.1974	Oromia	Region	Amhara	2007
Ethiopia	Aman Mikael Andom	12.09.1974	23.11.1974	Eritrea*	Region	Amhara	2007
Ethiopia	Tafari Benti	28.11.1974	03.02.1977	n/a	Region	Oroma	2007
Ethiopia	Mengistu Haile Mariam	11.02.1977	21.05.1991	n/a	Region	Amhara	2007
Ethiopia	Tesfaye Gebre Kidan Geletu	21.05.1991	27.05.1991	n/a	Region	Amhara	2007
Ethiopia	Meles Zenawi Asres	27.05.1991	20.08.2012	Tigray Region	Region	Tigry	2007
Ethiopia	Hailemariam Desalegn Boshe	20.08.2012	02.04.2018	SNNPR	Region	SNNP	2007
Ethiopia	Abiy Ahmed Ali[e]	02.04.2018	in office[d]	Oromia	Region	Oroma	2007
Greece	Konstantinos G. Karamanlis	04.11.1961	11.06.1963	Central Macedonia	Region		
Greece	Panagiotis Pipinelis	17.06.1963	29.09.1963	Attica	Region		
Greece	Stylianos Mavromichalis	29.09.1963	08.11.1963	n/a	Region		
Greece	Georgios Papandreou	08.11.1963	24.12.1963	Western Greece	Region		
Greece	Ioannis Paraskevopoulos	31.12.1963	18.02.1964	Western Greece	Region		
Greece	Georgios Papandreou	18.02.1964	15.07.1965	Western Greece	Region		
Greece	Georgios Athanasiadis–Novas	15.07.1965	05.08.1965	n/a	Region		
Greece	Ilias Tsirimokos	20.08.1965	29.08.1965	n/a	Region		
Greece	Stefanos Stefanopoulos	17.09.1965	22.12.1966	Western Greece	Region		
Greece	Ioannis Paraskevopoulos	22.12.1966	30.03.1967	Western Greece	Region		
Greece	Panagiotis Kanellopoulos	03.04.1967	21.04.1967	Western Greece	Region		
Greece	Konstantinos Kollias	21.04.1967	13.12.1967	Peloponnese	Region		
Greece	Georgios Papadopoulos	13.12.1967	25.11.1973	Western Greece	Region		
Greece	Dimitrios Ioannidis	25.11.1973	24.07.1974	Attica	Region		
Greece	Konstantinos G. Karamanlis	24.07.1974	09.05.1980	Central Macedonia	Region		
Greece	Georgios Ioannou Rallis	09.05.1980	21.10.1981	Attica	Region		
Greece	Andreas Georgios Papandreou	21.10.1981	02.07.1989	North Aegean	Region		
Greece	Tzannis Tzannetakis	02.07.1989	11.10.1989	n/a	Region		
Greece	Ioannis Grivas	11.10.1989	23.11.1989	n/a	Region		
Greece	Xenophon Zolotas	28.11.1989	10.04.1990	Attica	Region		
Greece	Konstantinos Mitsotakis	11.04.1990	13.10.1993	Crete	Region		
Greece	Andreas Georgios Papandreou	13.10.1993	20.11.1995	North Aegean	Region		
Greece	Apostolos Tsochatzopoulos	20.11.1995	22.01.1996	Attica	Region		
Greece	Konstantinos G. Simitis	22.01.1996	10.03.2004	Attica	Region		
Greece	Kostas Karamanlis	10.03.2004	06.10.2009	Attica	Region		
Greece	George Andreas Papandreou	06.10.2009	11.11.2011	United States*	Region		
Greece	Lucas Demetrios Papademos	11.11.2011	16.05.2012	Attica	Region		
Greece	Panagiotis Pikrammenos	16.05.2012	20.06.2012	n/a	Region		
Greece	Antonis Samaras	20.06.2012	26.01.2015	Attica	Region		
Greece	Alexis Tsipras	26.01.2015	in office[d]	Attica	Region		
Guatemala	Miguel Ydígoras Fuentes	02.03.1958	31.03.1963	Retalhuleu	Department	Ladino	2015
Guatemala	Alfredo Enrique Peralta Azurdia	31.03.1963	01.07.1966	Guatemala	Department	Ladino	2015
Guatemala	Julio César Méndez Montenegro	01.07.1966	01.07.1970	n/a	Department	Ladino	2015
Guatemala	Carlos Manuel Arana Osorio	01.07.1970	01.07.1974	Santa Rosa	Department	Ladino	2015
Guatemala	Kjell Eugenio Laugerud García	01.07.1974	01.07.1978	Guatemala	Department	Ladino	2015
Guatemala	Fernando Romeo Lucas García	01.07.1978	23.03.1982	Alta Verapaz	Department	Ladino	2015
Guatemala	José Efraín Ríos Montt	23.03.1982	08.08.1983	Huehuetenango	Department	Ladino	2015

Guatemala	Óscar Humberto Mejía Víctores	08.08.1983	14.01.1986	n/a	Department	Ladino	2015
Guatemala	Marco Vinicio Cerezo Arévalo	14.01.1986	14.01.1991	Guatemala	Department	Ladino	2015
Guatemala	Jorge Antonio Serrano Elías	14.01.1991	31.05.1993	Guatemala	Department	Ladino	2015
Guatemala	Gustavo Adolfo Espina Salguero	31.05.1993	01.06.1993	n/a	Department	Ladino	2015
Guatemala	Ramiro de León Carpio	01.06.1993	14.01.1996	Guatemala	Department	Ladino	2015
Guatemala	Álvaro Enrique Arzú Yrigoyen	14.01.1996	14.01.2000	Guatemala	Department	Ladino	2015
Guatemala	Alfonso Antonio Portillo Cabrera	15.01.2000	14.01.2004	Zacapa	Department	Ladino	2015
Guatemala	Óscar Berger Perdomo	14.01.2004	14.01.2008	Guatemala	Department	Ladino	2015
Guatemala	Álvaro Colom Caballeros	14.01.2008	14.01.2012	Guatemala	Department	Ladino	2015
Guatemala	Otto Fernando Pérez Molina	14.01.2012	03.09.2015	Guatemala	Department	Ladino	2015
Guatemala	Alejandro Maldonado[e]	03.09.2015	14.01.2016	Guatemala	Department	Ladino	2015
Guatemala	Jimmy Morales[e]	14.01.2016	in office[d]	Guatemala	Department	Ladino	2015
Haiti	François Duvalier	15.10.1957	22.04.1971	Ouest	Department		
Haiti	Jean-Claude Duvalier	22.04.1971	07.02.1986	Ouest	Department		
Haiti	Henri Namphy	07.02.1986	07.02.1988	Nord	Department		
Haiti	Leslie François Saint Roc Manigat	07.02.1988	20.06.1988	Ouest	Department		
Haiti	Henri Namphy	20.06.1988	17.09.1988	Nord	Department		
Haiti	Matthieu Prosper Avril	17.09.1988	10.03.1990	n/a	Department		
Haiti	Hérard Abraham	10.03.1990	13.03.1990	n/a	Department		
Haiti	Ertha Pascal-Trouillot	13.03.1990	07.02.1991	Ouest	Department		
Haiti	Jean-Bertrand Aristide	07.02.1991	30.09.1991	Sud	Department		
Haiti	Joseph Raoul Cédras	30.09.1991	14.10.1994	n/a	Department		
Haiti	Jean-Bertrand Aristide	15.10.1994	07.02.1996	Sud	Department		
Haiti	René Garcia Préval	07.02.1996	07.02.2001	Ouest	Department		
Haiti	Jean-Bertrand Aristide	08.02.2001	29.02.2004	Sud	Department		
Haiti	Boniface Alexandre	29.02.2004	14.05.2006	Ouest	Department		
Haiti	René Garcia Préval	14.05.2006	14.05.2011	Ouest	Department		
Haiti	Michel Joseph Martelly	14.05.2011	07.02.2016	Ouest	Department		
Haiti	Jocelerme Privert[e]	14.02.2016	07.02.2017	Nippes	Department		
Haiti	Jovenel Moïse[e]	07.02.2017	in office[d]	Nord-Est	Department		
Honduras	Oswaldo Enrique López Arellano	03.10.1963	06.06.1971	El Paraíso	Department	White/Mestizo	2001
Honduras	Ramón Ernesto Cruz Uclés	06.06.1971	04.12.1972	Francisco Morazán	Department	White/Mestizo	2001
Honduras	Oswaldo Enrique López Arellano	04.12.1972	22.04.1975	El Paraíso	Department	White/Mestizo	2001
Honduras	Juan Alberto Melgar Castro	22.04.1975	07.08.1978	n/a	Department	White/Mestizo	2001
Honduras	Policarpo Juan Paz García	07.08.1978	27.01.1982	Valle	Department	White/Mestizo	2001
Honduras	Roberto Suazo Córdova	27.01.1982	27.01.1986	La Paz	Department	White/Mestizo	2001
Honduras	José Simón Azcona del Hoyo	27.01.1986	27.01.1990	Atlántida	Department	White/Mestizo	2001
Honduras	Rafael Leonardo Callejas Romero	27.01.1990	27.01.1994	Francisco Morazán	Department	White/Mestizo	2001
Honduras	Carlos Roberto Reina Idiáquez	27.01.1994	27.01.1998	Francisco Morazán	Department	White/Mestizo	2001
Honduras	Carlos Roberto Flores Facussé	27.01.1998	27.01.2002	Francisco Morazán	Department	White/Mestizo	2001
Honduras	Ricardo Rodolfo Maduro Joest[b]	27.01.2002	27.01.2006	Francisco Morazán	Department	White/Mestizo	2001
Honduras	José Manuel Zelaya Rosales	27.01.2006	28.06.2009	Olancho	Department	White/Mestizo	2001
Honduras	Roberto Micheletti Baín	28.06.2009	27.01.2010	n/a	Department	White/Mestizo	2001
Honduras	Porfirio Lobo Sosa	27.01.2010	27.01.2014	Colón	Department	White/Mestizo	2001
Honduras	Juan Orlando Hernández Alvarado	27.01.2014	in office[d]	Lempira	Department	White/Mestizo	2001
India	Jawaharlal Nehru	15.08.1947	27.05.1964	Uttar Pradesh	State	Hindustani-Hindu	2006
India	Gulzarilal Nanda	27.05.1964	09.06.1964	Pakistan*	State	Punjabi-Hindu	2006
India	Lal Bahadur Shastri	09.06.1964	11.01.1966	Uttar Pradesh	State	Hindustani-Hindu	2006
India	Gulzarilal Nanda	11.01.1966	24.01.1966	Pakistan*	State	Punjabi-Hindu	2006
India	Indira Priyadarshini Gandhi	24.01.1966	22.03.1977	Uttar Pradesh	State	Hindustani-Hindu	2006
India	Morarji Desai	24.03.1977	15.06.1979	Gujarat	State	Gujarati-Hindu	2006
India	Chaudhary Charan Singh	28.07.1979	14.01.1980	Uttar Pradesh	State	OBC	2006
India	Indira Priyadarshini Gandhi	14.01.1980	31.10.1984	Uttar Pradesh	State	Hindustani-Hindu	2006
India	Rajiv Ratna Gandhi	31.10.1984	02.12.1989	Maharashtra	State	Hindustani-Hindu	2006
India	Vishwanath Pratap Singh	02.12.1989	10.11.1990	Uttar Pradesh	State	Hindustani-Hindu	2006
India	Chandra Shekhar Singh	10.11.1990	21.06.1991	Uttar Pradesh	State	Hindustani-Hindu	2006
India	P.V. Narasimha Rao	21.06.1991	16.05.1996	Telangana	State	Telugu-Hindu	2006
India	Atal Bihari Vajpayee	16.05.1996	01.06.1996	Madhya Pradesh	State	Hindustani-Hindu	2006
India	H.D. Deve Gowda	01.06.1996	21.04.1997	Karnataka	State	OBC	2006
India	Inder Kumar Gujral	21.04.1997	19.03.1998	Pakistan*	State	Punjabi-Hindu	2006
India	Atal Bihari Vajpayee	19.03.1998	22.05.2004	Madhya Pradesh	State	Hindustani-Hindu	2006
India	Manmohan Singh	22.05.2004	26.05.2014	Pakistan*	State	Punjabi-Sikh	2006
India	Narendra Damodardas Modi	29.05.2014	in office[d]	Gujarat	State	OBC	2006
Indonesia	Sukarno	27.12.1949	12.03.1966	Jawa Timur	Province	Javanese	2010
Indonesia	Muhammad Suharto	12.03.1966	21.05.1998	Yogyakarta	Province	Javanese	2010
Indonesia	Bacharuddin Jusuf Habibie	21.05.1998	20.10.1999	South Sulawesi	Province	Bugis	2010
Indonesia	Abdurrahman Wahid	20.10.1999	23.07.2001	Jawa Timur	Province	Javanese	2010
Indonesia	Megawati Sukarnoputri	24.07.2001	20.10.2004	Yogyakarta	Province	Javanese	2010
Indonesia	Susilo Bambang Yudhoyono	20.10.2004	20.10.2014	Jawa Timur	Province	Javanese	2010
Indonesia	Joko Widodo	20.10.2014	in office[d]	Jawa Tengah	Province	Javanese	2010
Iran	Mohammad Reza Pahlavi	19.08.1953	16.01.1979	Tehran	Province (2012)		
Iran	Ruhollah Khomeini	01.02.1979	03.06.1989	Markazi	Province (2012)		
Iran	Sayyid Ali Hosseini Khamenei	04.06.1989	03.08.1989	Razavi Khorasan	Province (2012)		
Iran	Akbar Hashemi Rafsanjani	17.08.1989	03.08.1997	Kerman	Province (2012)		
Iran	Mohammad Khatami	03.08.1997	03.08.2005	Yazd	Province (2012)		
Iran	Mahmoud Ahmadinejad	03.08.2005	03.08.2013	Semnan	Province (2012)		
Iran	Hassan Rouhani	03.08.2013	in office[d]	Semnan	Province (2012)		
Kenya	Jomo Kenyatta	12.12.1963	22.08.1978	Central	Province (2012)	Kikuyu	2014
Kenya	Daniel Toroitich arap Moi	22.08.1978	30.12.2002	Rift Valley	Province (2012)	Kalenjin	2014
Kenya	Mwai Kibaki	31.12.2002	09.04.2013	Central	Province (2012)	Kikuyu	2014
Kenya	Uhuru Muigai Kenyatta	09.04.2013	in office[d]	Nairobi	Province (2012)	Kikuyu	2014
Madagascar	Philibert Tsiranana	26.06.1960	08.10.1972	Mahajanga	Province (2008)		
Madagascar	Gabriel Ramanantsoa	12.10.1972	05.02.1975	Antananarivo	Province (2008)		
Madagascar	Richard Ratsimandrava	05.02.1975	11.02.1975	Antananarivo	Province (2008)		
Madagascar	Gilles Andriamahazo	11.02.1975	15.06.1975	Toliary	Province (2008)		
Madagascar	Didier Ratsiraka	15.06.1975	27.03.1993	Toamasina	Province (2008)		
Madagascar	Albert Zafy	27.03.1993	05.09.1996	Antsiranana	Province (2008)		

Madagascar	Norbert Lala Ratsirahonana	05.09.1996	09.02.1997	n/a	Province (2008)		
Madagascar	Didier Ratsiraka	09.02.1997	06.07.2002	Toamasina	Province (2008)		
Madagascar	Marc Ravalomanana	06.07.2002	17.03.2009	Antananarivo	Province (2008)		
Madagascar	Andry Nirina Rajoelina	17.03.2009	25.01.2014	Antananarivo	Province (2008)		
Madagascar	Hery Rajaonarimampianina	25.01.2014	in office[d]	Antananarivo	Province (2008)		
Malawi	Hastings Kamuzu Banda	06.07.1964	21.05.1994	Kasungu	District	Chewa	2008
Malawi	Elson Bakili Muluzi	21.05.1994	24.05.2004	Machinga	District	Yao	2008
Malawi	Bingu wa Mutharika	24.05.2004	07.04.2012	Thyolo	District	Lomwe	2008
Malawi	Joyce Hilda Banda	07.04.2012	31.05.2014	Zomba	District	Yao	2008
Malawi	Arthur Peter Mutharika	31.05.2014	in office[d]	Thyolo	District	Lomwe	2008
Malaysia	Tunku Abdul Rahman	21.08.1959	22.09.1970	Kedah	State	Sinhalese	91,00
Malaysia	Abdul Razak Hussein	22.09.1970	14.01.1976	Pahang	State	Sinhalese	91,00
Malaysia	Hussein bin Dato' Onn	14.01.1976	16.07.1981	Johor	State	Sinhalese	91,00
Malaysia	Mahathir bin Mohamad	16.07.1981	31.10.2003	Kedah	State	Sinhalese	91,00
Malaysia	Abdullah Ahmad Badawi	31.10.2003	03.04.2009	Pulau Pinang	State	Sinhalese	91,00
Malaysia	Najib Razak	03.04.2009	10.05.2018	Pahang	State	Sinhalese	91,00
Malaysia	Mahathir bin Mohamad[e]	10.05.2018	in office[d]	Kedah	State	Sinhalese	91,00
Mexico	Adolfo López Mateos	01.12.1958	01.12.1964	México	State	Mestizo	2015
Mexico	Gustavo Díaz Ordaz Bolaños	01.12.1964	01.12.1970	Puebla	State	Mestizo	2015
Mexico	Luis Echeverría Álvarez	01.12.1970	01.12.1976	Federal Distrito	State	Mestizo	2015
Mexico	José López Portillo	01.12.1976	01.12.1982	Federal Distrito	State	Mestizo	2015
Mexico	Miguel de la Madrid Hurtado	01.12.1982	01.12.1988	Colima	State	Mestizo	2015
Mexico	Carlos Salinas de Gortari	01.12.1988	30.11.1994	Federal District	State	Mestizo	2015
Mexico	Ernesto Zedillo Ponce de León	01.12.1994	30.11.2000	Federal District	State	Mestizo	2015
Mexico	Vicente Fox Quesada	01.12.2000	30.11.2006	Federal District	State	Mestizo	2015
Mexico	Felipe Calderón Hinojosa	01.12.2006	01.12.2012	Michoacán	State	Mestizo	2015
Mexico	Enrique Peña Nieto	01.12.2012	in office[d]	México	State	Mestizo	2015
Mozambique	Samora Moisés Machel	25.06.1975	19.10.1986	Gaza	Province	Tsonga	2007
Mozambique	Joaquim Alberto Chissano	06.11.1986	02.02.2005	Gaza	Province	Tsonga	2007
Mozambique	Armando Emílio Guebuza	02.02.2005	15.01.2015	Nampula	Province	Tsonga	2007
Mozambique	Filipe Jacinto Nyusi	15.01.2015	in office[d]	Cabo Delgado	Province	Makonde	2007
Myanmar	Ne Win	02.03.1962	25.07.1988	Bago	State		
Myanmar	Sein Lwin	25.07.1988	12.08.1988	n/a	State		
Myanmar	Maung Maung	19.08.1988	18.09.1988	n/a	State		
Myanmar	Saw Maung	18.09.1988	23.04.1992	Mandalay	State		
Myanmar	Than Shwe	23.04.1992	30.03.2011	Mandalay	State		
Myanmar	Thein Sein	30.03.2011	30.03.2016	Ayeyarwady	State		
Myanmar	Htin Kyaw[e]	30.03.2016	06.04.2016	Yangon	State		
Myanmar	Aung San Suu Kyi[e]	06.04.2016	in office[d]	Yangon	State		
Nepal	Mahendra Bir Bikram Shah Dev	14.03.1955	31.01.1972	Central	Dev. R. (2014)	Royal	01,06,11
Nepal	Birendra Bakron Alkaff Shah	31.01.1972	09.11.1990	Central	Dev. R. (2014)	Royal	01,06,11
Nepal	Krishna Prasad Bhattarai	09.11.1990	26.05.1991	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Girija Prasad Koirala	26.05.1991	30.11.1994	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Man Mohan Adhikari	30.11.1994	12.09.1995	n/a	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Sher Bahadur Deuba	12.09.1995	12.03.1997	Far-West	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Lokendra Bahadur Chand	12.03.1997	07.10.1997	Far-West	Dev. R. (2014)	n/a	01,06,11
Nepal	Surya Bahadur Thapa	07.10.1997	15.04.1998	East	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Girija Prasad Koirala	15.04.1998	31.05.1999	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Krishna Prasad Bhatterai	31.05.1999	22.03.2000	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Girija Prasad Koirala	22.03.2000	26.07.2001	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Sher Bahadur Deuba	26.07.2001	04.10.2002	Far-West	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Lokendra Bahadur Chand	11.10.2002	05.06.2003	Far-West	Dev. R. (2014)	n/a	01,06,11
Nepal	Surya Bahadur Thapa	05.06.2003	03.06.2004	East	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Sher Bahadur Deuba	03.06.2004	01.02.2005	Far-West	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Gyanendra Bir Bikram Shah Dev	01.02.2005	30.04.2006	Central	Dev. R. (2014)	Royal	01,06,11
Nepal	Girija Prasad Koirala	30.04.2006	18.08.2008	India*	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Pushpa Kamal Dahal	18.08.2008	25.05.2009	West	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Madhav Kumar Nepal	25.05.2009	06.02.2011	Central	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Jhala Nath Khanal	06.02.2011	29.08.2011	East	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Baburam Bhattarai	29.08.2011	14.03.2013	West	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Khil Raj Regmi	14.03.2013	11.02.2014	West	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Sushil Koirala	11.02.2014	10.10.2015	East	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Khadga Prasad Sharma Oli	10.10.2015	04.08.2016	East	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Pushpa Kamal Dahal[e]	04.08.2016	07.06.2017	West	Dev. R. (2014)	Hill Brahmin	01,06,11
Nepal	Sher Bahadur Deuba[e]	07.06.2017	15.02.2018	Far-West	Dev. R. (2014)	Hill Chhetri	01,06,11
Nepal	Khadga Prasad Sharma Oli[e]	15.02.2018	in office[d]	East	Dev. R. (2014)	Hill Brahmin	01,06,11
Nicaragua	Luis Anastasio Somoza Debayle	29.09.1956	01.05.1963	León	Department	White/Mestizo	2005
Nicaragua	René Schick Gutiérrez	01.05.1963	03.08.1966	Managua	Department	White/Mestizo	2005
Nicaragua	Lorenzo Guerrero Gutiérrez	04.08.1966	01.05.1967	Granada	Department	White/Mestizo	2005
Nicaragua	Anastasio Somoza Debayle	01.05.1967	17.07.1979	León	Department	White/Mestizo	2005
Nicaragua	José Daniel Ortega Saavedra	18.07.1979	25.04.1990	Chontales	Department	White/Mestizo	2005
Nicaragua	Violeta Barrios de Chamorro	25.04.1990	10.01.1997	Rivas	Department	White/Mestizo	2005
Nicaragua	José Arnoldo Alemán Lacayo	10.01.1997	10.01.2002	Managua	Department	White/Mestizo	2005
Nicaragua	Enrique José Bolaños Geyer	11.01.2002	10.01.2007	Masaya	Department	White/Mestizo	2005
Nicaragua	José Daniel Ortega Saavedra	10.01.2007	in office[d]	Chontales	Department	White/Mestizo	2005
Niger	Hamani Diori	03.10.1960	15.04.1974	Niamey	Region	Djerma-Songhai	92,06
Niger	Seyni Kountché	17.04.1974	10.11.1987	Tillabéri	Region	Djerma-Songhai	92,06
Niger	Ali Saibou	10.11.1987	16.04.1993	Tillabéri	Region	Djerma-Songhai	92,06
Niger	Mahamane Ousmane	16.04.1993	27.01.1996	Zinder	Region	Kanouri	92,06
Niger	Ibrahim Baré Maïnassara	27.01.1996	11.04.1999	Maradi	Region	Housa	92,06
Niger	Daouda Malam Wanké	11.04.1999	22.12.1999	Burkina Faso*	Region	Housa	92,06
Niger	Mamadou Tandja	22.12.1999	08.02.2010	Diffa	Region	Kanouri	92,06
Niger	Salou Djibo	08.02.2010	07.04.2011	Tillabéri	Region	Djerma-Songhai	92,06
Niger	Mahamadou Issoufou	07.04.2011	in office[d]	Tahoua	Region	Housa	92,06
Nigeria	Abubakar Tafawa Balewa	01.10.1960	15.01.1966	Bauchi	State	Hausa-Fulani	2008
Nigeria	Johnson Aguiyi-Ironsi	15.01.1966	29.07.1966	n/a	State	Igbo	2008
Nigeria	Yakubu Dan-Yumma Gowon	29.07.1966	29.07.1975	Plateau	State	Angas	2008

Nigeria	Murtala Muhammed	29.07.1975	13.02.1976	n/a	State	Hausa-Fulani	2008
Nigeria	Olusegun Obasanjo	13.02.1976	01.10.1979	Ogun	State	Yoruba	2008
Nigeria	Shehu Usman Aliyu Shagari	01.10.1979	31.12.1983	Sokoto	State	Hausa-Fulani	2008
Nigeria	Muhammadu Buhari	31.12.1983	27.08.1985	Katsina	State	Hausa-Fulani	2008
Nigeria	Ibrahim Badamasi Babangida	27.08.1985	26.08.1993	Niger	State	Gwari	2008
Nigeria	Ernest Shonekan	26.08.1993	17.11.1993	n/a	State	Yoruba	2008
Nigeria	Sani Abacha	17.11.1993	08.06.1998	Kano	State	Kanuri	2008
Nigeria	Abdulsalami Abubakar	09.06.1998	29.05.1999	Niger	State	Gwari	2008
Nigeria	Olusegun Obasanjo	29.05.1999	29.05.2007	Ogun	State	Yoruba	2008
Nigeria	Umaru Musa Yar'Adua	29.05.2007	09.02.2010	Katsina	State	Hausa-Fulani	2008
Nigeria	Goodluck Jonathan	09.02.2010	29.05.2015	Bayelsa	State	Ijaw	2008
Nigeria	Muhammadu Buhari	29.05.2015	in office[d]	Katsina	State	Hausa-Fulani	2008
Pakistan	Ayub Khan	07.10.1958	25.03.1969	NWFP	Province	Pashtun	1998
Pakistan	Yahya Khan	31.03.1969	20.12.1971	Punjab	Province	Pashtun	1998
Pakistan	Zulfikar Ali Bhutto	20.12.1971	05.07.1977	Sind	Province	Sindhi	1998
Pakistan	Muhammad Zia-ul-Haq	05.07.1977	17.08.1988	India*	Province	Punjabi	1998
Pakistan	Ghulam Ishaq Khan	17.08.1988	02.12.1988	n/a	Province	Pashtun	1998
Pakistan	Benazir Bhutto	02.12.1988	06.08.1990	Sind	Province	Sindhi	1998
Pakistan	Ghulam Mustafa Jatoi	06.08.1990	06.11.1990	n/a	Province	Sindhi	1998
Pakistan	Mian Muhammad Nawaz Sharif	06.11.1990	18.04.1993	Punjab	Province	Punjabi	1998
Pakistan	Sardar Mir Balakh Sher Mazari	18.04.1993	26.05.1993	n/a	Province	Baluchi	1998
Pakistan	Mian Muhammad Nawaz Sharif	26.05.1993	18.07.1993	Punjab	Province	Punjabi	1998
Pakistan	Moeenuddin Ahmad Qureshi	19.07.1993	19.10.1993	n/a	Province	n/a	1998
Pakistan	Benazir Bhutto	19.10.1993	05.11.1996	Sind	Province	Sindhi	1998
Pakistan	Malik Meraj Khalid	05.11.1996	17.02.1997	n/a	Province	Punjabi	1998
Pakistan	Mian Muhammad Nawaz Sharif	17.02.1997	12.10.1999	Punjab	Province	Punjabi	1998
Pakistan	Pervez Musharraf	14.10.1999	18.08.2008	India*	Province	Mohajir	1998
Pakistan	Muhammad Mian Soomro	18.08.2008	09.09.2008	n/a	Province	Sindhi	1998
Pakistan	Asif Ali Zardari	09.09.2008	05.06.2013	Sind	Province	Baluchi	1998
Pakistan	Mian Muhammad Nawaz Sharif	05.06.2013	28.07.2017	Punjab	Province	Punjabi	1998
Pakistan	Shahid Khaqan Abbasi[e]	01.08.2017	31.05.2018	Sind	Province	n/a	1998
Pakistan	Nasirul Mulk[e]	01.06.2018	in office[d]	NWFP	Province	n/a	1998
Panama	Ernesto de la Guardia Navarro	01.10.1956	01.10.1960	Panama	Province	White/Mestizo	2010
Panama	Roberto Francisco Chiari Remón	01.10.1960	01.10.1964	Panama	Province	White/Mestizo	2010
Panama	Marco Aurelio Robles Méndez	01.10.1964	01.10.1968	Coclé	Province	White/Mestizo	2010
Panama	Arnulfo Arias Madrid	01.10.1968	12.10.1968	Coclé	Province	White/Mestizo	2010
Panama	Omar Efraín Torrijos Herrera	12.10.1968	31.07.1981	Veraguas	Province	White/Mestizo	2010
Panama	Florencio Flores Aguilar	31.07.1981	03.03.1982	n/a	Province	White/Mestizo	2010
Panama	Rubén Darío Paredes del Río	03.03.1982	15.08.1983	n/a	Province	White/Mestizo	2010
Panama	Manuel Antonio Noriega Moreno	15.08.1983	03.01.1990	Panama	Province	White/Mestizo	2010
Panama	Guillermo David Endara Galimany	04.01.1990	01.09.1994	Panama	Province	White/Mestizo	2010
Panama	Ernesto Pérez Balladares	01.09.1994	01.09.1999	Panama	Province	White/Mestizo	2010
Panama	Mireya Elisa Moscoso Rodríguez	01.09.1999	01.09.2004	Los Santos	Province	White/Mestizo	2010
Panama	Martín Erasto Torrijos Espino	01.09.2004	01.07.2009	Panama	Province	White/Mestizo	2010
Panama	Ricardo Alberto Martinelli Berroca	01.07.2009	01.07.2014	Panama	Province	White/Mestizo	2010
Panama	Juan Carlos Varela Rodríguez	01.07.2014	in office[d]	Panama	Province	White/Mestizo	2010
Papua N. Guinea	Michael Thomas Somare	16.09.1975	11.03.1980	East New Britain	Province		
Papua N. Guinea	Julius Chan	11.03.1980	02.08.1982	New Ireland	Province		
Papua N. Guinea	Michael Thomas Somare	02.08.1982	21.11.1985	East New Britain	Province		
Papua N. Guinea	Paias Wingti	21.11.1985	04.07.1988	n/a	Province		
Papua N. Guinea	Rabbie Langanai Namaliu	04.07.1988	17.07.1992	East New Britain	Province		
Papua N. Guinea	Paias Wingti	17.07.1992	30.08.1994	n/a	Province		
Papua N. Guinea	Julius Chan	30.08.1994	22.07.1997	New Ireland	Province		
Papua N. Guinea	William Jack Skate	22.07.1997	14.07.1999	Gulf	Province		
Papua N. Guinea	Mekere Morauta	14.07.1999	05.08.2002	Gulf	Province		
Papua N. Guinea	Michael Thomas Somare	06.08.2002	02.08.2011	East New Britain	Province		
Papua N. Guinea	Peter Charles Paire O'Neill	02.08.2011	in office[d]	South. Highlands	Province		
Peru	Manuel Prado y Ugarteche	28.07.1956	19.07.1962	Lima province	Department	White/Mestizo	93,07
Peru	Ricardo Pío Pérez Godoy	19.07.1962	03.03.1963	n/a	Department	White/Mestizo	93,07
Peru	Nicolás Eduardo Lindley López	03.03.1963	28.07.1963	n/a	Department	White/Mestizo	93,07
Peru	Fernando Belaúnde Terry	28.07.1963	03.10.1968	Lima province	Department	White/Mestizo	93,07
Peru	Juan Francisco Velasco Alvarado	03.10.1968	29.08.1975	Piura	Department	White/Mestizo	93,07
Peru	Francisco Morales Bermúdez	30.08.1975	28.07.1980	Lima province	Department	White/Mestizo	93,07
Peru	Fernando Belaúnde Terry	28.07.1980	28.07.1985	Lima province	Department	White/Mestizo	93,07
Peru	Alan Gabriel Ludwig García Pérez	28.07.1985	28.07.1990	Lima province	Department	White/Mestizo	93,07
Peru	Alberto Kenya Fujimori Fujimori	28.07.1990	22.11.2000	Lima province	Department	Japanese	93,07
Peru	Valentín Paniagua Corazao	23.11.2000	28.07.2001	Cusco	Department	White/Mestizo	93,07
Peru	Alejandro Toledo Manrique	28.07.2001	28.07.2006	Ancash	Department	Quechua	93,07
Peru	Alan García Pérez	28.07.2006	28.07.2011	Lima province	Department	White/Mestizo	93,07
Peru	Ollanta Moisés Humala Tasso[c]	28.07.2011	28.07.2016	Lima province	Department	White/Mestizo	93,07
Peru	Pedro Pablo Kuczynski Godard[e]	28.07.2016	23.05.2018	Lima province	Department	White/Mestizo	93,07
Peru	Martín Alberto Vizcarra Cornejo[e]	23.05.2018	in office[d]	n/a	Department	n/a	93,07
Philippines	Carlos Polistico Garcia	17.03.1957	14.11.1961	Central Visayas	Region (2016)	Christian Lowland	2000
Philippines	Diosdado Pangan Macapagal	14.11.1961	30.12.1965	Central Luzon	Region (2016)	Christian Lowland	2000
Philippines	Ferdinand Marcos	30.12.1965	25.02.1986	Ilocos	Region (2016)	Christian Lowland	2000
Philippines	Corazon Aquino	25.02.1986	30.06.1992	Central Luzon	Region (2016)	Christian Lowland	2000
Philippines	Fidel Valdez Ramos	30.06.1992	30.06.1998	Ilocos	Region (2016)	Christian Lowland	2000
Philippines	Joseph Ejercito Estrada	30.06.1998	20.01.2001	Nat. Capital Reg.	Region (2016)	Christian Lowland	2000
Philippines	Gloria Macapagal-Arroyo	21.01.2001	30.06.2010	Nat. Capital Reg.	Region (2016)	Christian Lowland	2000
Philippines	Benigno Aquino III	30.06.2010	30.06.2016	Nat. Capital Reg.	Region (2016)	Christian Lowland	2000
Philippines	Rodrigo Duterte[e]	30.06.2016	in office[d]	Eastern Visayas	Region (2016)	Christian Lowland	2000
Romania	Gheorghe Gheorghiu-Dej	30.12.1947	19.03.1965	Vaslui	County	Romanian	92,02,11
Romania	Nicolae Ceaușescu	22.03.1965	25.12.1989	Olt	County	Romanian	92,02,11
Romania	Petre Roman	26.12.1989	01.10.1991	Bucharest	County	Romanian	92,02,11
Romania	Theodor Dumitru Stolojan	01.10.1991	04.11.1992	Dâmbovița	County	Romanian	92,02,11
Romania	Nicolae Văcăroiu	04.11.1992	12.12.1996	n/a	County	Romanian	92,02,11
Romania	Victor Ciorbea	12.12.1996	30.03.1998	Alba	County	Romanian	92,02,11

Romania	Gavril Dejeu	30.03.1998	15.04.1998	n/a	County	Romanian	92,02,11
Romania	Radu Vasile	15.04.1998	14.12.1999	Sibiu	County	Romanian	92,02,11
Romania	Alexandru Athanasiu	14.12.1999	22.12.1999	n/a	County	Romanian	92,02,11
Romania	Constantin Mugur Isărescu	22.12.1999	28.12.2000	Vâlcea	County	Romanian	92,02,11
Romania	Adrian Năstase	28.12.2000	21.12.2004	Bucharest	County	Romanian	92,02,11
Romania	Eugen Bejinariu	21.12.2004	29.12.2004	n/a	County	n/a	92,02,11
Romania	Traian Băsescu	29.12.2004	20.04.2007	Constanța	County	Romanian	92,02,11
Romania	Nicolae Văcăroiu	20.04.2007	23.05.2007	n/a	County	n/a	92,02,11
Romania	Traian Băsescu	23.05.2007	10.07.2012	Constanța	County	Romanian	92,02,11
Romania	Crin Antonescu	10.07.2012	28.08.2012	n/a	County	n/a	92,02,11
Romania	Traian Băsescu	28.08.2012	21.12.2014	Constanța	County	Romanian	92,02,11
Romania	Klaus Iohannis[e]	21.12.2014	in office[d]	Sibiu	County	German	92,02,11
South Africa	Hendrik Frensch Verwoerd	03.09.1958	06.09.1966	Netherlands*	Province	Afrikaner	01,11
South Africa	Theophilus E. Dönges	06.09.1966	13.09.1966	n/a	Province	Afrikaner	01,11
South Africa	Balthazar Johannes Vorster	13.09.1966	28.09.1978	Eastern Cape	Province	Afrikaner	01,11
South Africa	Pieter Willem Botha	28.09.1978	18.01.1989	Free State	Province	Afrikaner	01,11
South Africa	Jan Christiaan Heunis	19.01.1989	15.03.1989	n/a	Province	Afrikaner	01,11
South Africa	Pieter Willem Botha	15.03.1989	14.08.1989	Free State	Province	Afrikaner	01,11
South Africa	Frederik Willem de Klerk	15.08.1989	10.05.1994	Gauteng	Province	Afrikaner	01,11
South Africa	Nelson Rolihlahla Mandela	10.05.1994	16.06.1999	Eastern Cape	Province	Xhosa	01,11
South Africa	Thabo Mvuyelwa Mbeki	16.06.1999	25.09.2008	Eastern Cape	Province	Xhosa	01,11
South Africa	Kgalema Petrus Motlanthe	25.09.2008	09.05.2009	Gauteng	Province	Pedi	01,11
South Africa	Jacob Gedleyihlekisa Zuma	09.05.2009	14.02.2018	KwaZulu-Natal	Province	Zulu	01,11
South Africa	Cyril Ramaphosa[e]	14.02.2018	in office[d]	Gauteng	Province	Venda	01,11
Sri Lanka	Sirimavo Bandaranaike	22.07.1960	25.03.1965	Sabaragamuwa	Province		
Sri Lanka	Dudley Shelton Senanayake	25.03.1965	28.05.1970	West	Province		
Sri Lanka	Sirimavo Bandaranaike	31.05.1970	23.07.1977	Sabaragamuwa	Province		
Sri Lanka	Junius Richard Jayewardene	23.07.1977	02.01.1989	West	Province		
Sri Lanka	Ranasinghe Premadasa	02.01.1989	01.05.1993	West	Province		
Sri Lanka	Dingiri Banda Wijetunga	01.05.1993	12.11.1994	Central	Province		
Sri Lanka	Chandrika Kumaratunga	12.11.1994	19.11.2005	West	Province		
Sri Lanka	Percy Mahendra Rajapaksa	19.11.2005	09.01.2015	South	Province		
Sri Lanka	Maithripala Sirisena	09.01.2015	in office[d]	West	Province		
Sudan	El Ferik Ibrahim Abboud	18.11.1958	01.11.1964	Red Sea	State		
Sudan	Sirr Al-Khatim Al-Khalifa	01.11.1964	14.06.1965	n/a	State		
Sudan	Muhammad Ahmad Mahgoub	14.06.1965	25.07.1966	n/a	State		
Sudan	Sadiq al-Mahdi	26.07.1966	15.05.1967	Khartoum	State		
Sudan	Muhammad Ahmad Mahgoub	18.05.1967	23.05.1969	n/a	State		
Sudan	Jaafar Muhammad an-Nimeiry	25.05.1969	19.07.1971	Khartoum	State		
Sudan	Babiker an-Nur Osman	19.07.1971	22.07.1971	n/a	State		
Sudan	Jaafar Muhammad an-Nimeiry	22.07.1971	06.04.1985	Khartoum	State		
Sudan	Abdel Rahman Swar al-Dahab	06.04.1985	06.05.1986	n/a	State		
Sudan	Sadiq al-Mahdi	06.05.1986	30.06.1989	Khartoum	State		
Sudan	Omar Hassan Ahmad al-Bashir	30.06.1989	in office[d]	River Nile	State		
Tajikistan	Qadriddin Aslonov	31.08.1991	23.09.1991	n/a	Province	Tajik	2012
Tajikistan	Rahmon Nabiyevich Nabiyev	23.09.1991	07.09.1992	Sughd	Province	Tajik	2012
Tajikistan	Akbarsho Iskandarov	07.09.1992	20.11.1992	n/a	Province	Tajik	2012
Tajikistan	Emomali Rahmon	20.11.1992	in office[d]	Khatlon	Province	Tajik	2012
Tanzania	Julius Kambarage Nyerere	09.11.1961	05.11.1985	Mara	Region (2015)		
Tanzania	Ali Hassan Mwinyi	05.11.1985	05.11.1995	Pwani	Region (2015)		
Tanzania	Benjamin William Mkapa	05.11.1995	21.12.2005	Mtwara	Region (2015)		
Tanzania	Jakaya Mrisho Kikwete	21.12.2005	05.11.2015	Pwani	Region (2015)		
Tanzania	John Joseph Magufuli	05.11.2015	in office[d]	Geita	Region (2015)		
Thailand	Sarit Thanarat	20.10.1958	08.12.1963	Krung Thep	Province	Buddhist	70,80,90,00
Thailand	Thanom Kittikachorn	08.12.1963	13.10.1973	Tak	Province	Buddhist	70,80,90,00
Thailand	Sanya Dharmasakti	14.10.1973	21.02.1975	Krung Thep	Province	Buddhist	70,80,90,00
Thailand	Seni Pramoj	21.02.1975	06.03.1975	n/a	Province	Buddhist	70,80,90,00
Thailand	Kukrit Pramoj	17.03.1975	16.04.1976	Phitsanulok	Province	Buddhist	70,80,90,00
Thailand	Seni Pramoj	20.04.1976	06.10.1976	n/a	Province	Buddhist	70,80,90,00
Thailand	Sangad Chaloryu	06.10.1976	22.10.1976	n/a	Province	Buddhist	70,80,90,00
Thailand	Thanin Kraivichien	22.10.1976	20.10.1977	Krung Thep	Province	Buddhist	70,80,90,00
Thailand	Sangad Chaloryu	20.10.1977	12.11.1977	n/a	Province	n/a	70,80,90,00
Thailand	Kriangsak Chamanan	12.11.1977	29.02.1980	Samut Sakhon	Province	Buddhist	70,80,90,00
Thailand	Prem Tinsulanonda	03.03.1980	04.08.1988	Songkhla	Province	Buddhist	70,80,90,00
Thailand	Chatichai Choonhavan	04.08.1988	23.02.1991	Krung Thep	Province	Buddhist	70,80,90,00
Thailand	Anand Panyarachun	07.03.1991	04.04.1992	n/a	Province	Buddhist	70,80,90,00
Thailand	Suchinda Kraprayoon	05.04.1992	24.05.1992	n/a	Province	Buddhist	70,80,90,00
Thailand	Anand Panyarachun	10.06.1992	23.09.1992	n/a	Province	Buddhist	70,80,90,00
Thailand	Chuan Leekpai	23.09.1992	13.07.1995	Trang	Province	Buddhist	70,80,90,00
Thailand	Banharn Silpa-archa	13.07.1995	01.12.1996	Suphan Buri	Province	Buddhist	70,80,90,00
Thailand	Chavalit Yongchaiyudh	01.12.1996	09.11.1997	n/a	Province	Buddhist	70,80,90,00
Thailand	Chuan Leekpai	09.11.1997	09.02.2001	Trang	Province	Buddhist	70,80,90,00
Thailand	Thaksin Shinawatra	10.02.2001	19.09.2006	Chiang Mai	Province	Buddhist	70,80,90,00
Thailand	Surayud Chulanont	19.09.2006	29.01.2008	Prachinburi	Province	Buddhist	70,80,90,00
Thailand	Samak Sundaravej	29.01.2008	09.09.2008	Krung Thep	Province	Buddhist	70,80,90,00
Thailand	Somchai Wongsawat	09.09.2008	02.12.2008	Nakhon Si Tham.	Province	Buddhist	70,80,90,00
Thailand	Chaovarat Chanweerakul	02.12.2008	15.12.2008	n/a	Province	n/a	70,80,90,00
Thailand	Abhisit Vejjajiva	15.12.2008	08.08.2011	United Kingdom*	Province	Buddhist	70,80,90,00
Thailand	Yingluck Shinawatra	08.08.2011	07.05.2014	Chiang Mai	Province	Buddhist	70,80,90,00
Thailand	Niwatthamrong Boonsongpaisan	07.05.2014	22.05.2014	n/a	Province	n/a	70,80,90,00
Thailand	Prayut Chan-o-cha	22.05.2014	in office[d]	Nakhon Ratchas.	Province	Buddhist	70,80,90,00
Turkey	Mustafa İsmet İnönü	10.11.1961	13.02.1965	Izmir	Province	Turkish	2014
Turkey	Ali Suat Hayri Ürgüplü	13.02.1965	27.10.1965	Nevsehir	Province	Turkish	2014
Turkey	Süleyman Demirel	27.10.1965	12.03.1971	Isparta	Province	Turkish	2014
Turkey	İsmail Nihat Erim	19.03.1971	17.04.1972	Kocaeli	Province	Turkish	2014
Turkey	Ferit Sadi Melen	22.05.1972	15.04.1973	Van	Province	Turkish	2014
Turkey	Mehmet Naim Tal	15.04.1973	25.01.1974	Istanbul	Province	Turkish	2014

Turkey	Mustafa Bülent Ecevit	25.01.1974	07.11.1974	Istanbul	Province	Turkish	2014
Turkey	Mahmut Sadi Irmak	17.11.1974	31.03.1975	Konya	Province	Turkish	2014
Turkey	Süleyman Demirel	31.03.1975	21.06.1977	Isparta	Province	Turkish	2014
Turkey	Mustafa Bülent Ecevit	21.06.1977	21.07.1977	Istanbul	Province	Turkish	2014
Turkey	Süleyman Demirel	21.07.1977	21.12.1977	Isparta	Province	Turkish	2014
Turkey	Mustafa Bülent Ecevit	01.01.1978	12.11.1979	Istanbul	Province	Turkish	2014
Turkey	Süleyman Demirel	12.11.1979	20.09.1980	Isparta	Province	Turkish	2014
Turkey	Ahmet Kenan Evren	20.09.1980	23.11.1983	Manisa	Province	Turkish	2014
Turkey	Halil Turgut Özal	13.12.1983	09.11.1989	Malatya	Province	Turkish	2014
Turkey	Yıldırım Akbulut	09.11.1989	24.06.1991	Erzincan	Province	Turkish	2014
Turkey	Ahmet Mesut Yılmaz	24.06.1991	20.11.1991	Istanbul	Province	Turkish	2014
Turkey	Süleyman Demirel	20.11.1991	16.05.1993	Isparta	Province	Turkish	2014
Turkey	Erdal İnönü	16.05.1993	25.06.1993	Ankara	Province	Turkish	2014
Turkey	Tansu Çiller	25.06.1993	06.03.1996	Istanbul	Province	Turkish	2014
Turkey	Ahmet Mesut Yılmaz	06.03.1996	28.06.1996	Istanbul	Province	Turkish	2014
Turkey	Necmettin Erbakan	28.06.1996	30.06.1997	Sinop	Province	Turkish	2014
Turkey	Ahmet Mesut Yılmaz	30.06.1997	11.01.1999	Istanbul	Province	Turkish	2014
Turkey	Mustafa Bülent Ecevit	11.01.1999	18.11.2002	Istanbul	Province	Turkish	2014
Turkey	Abdullah Gül	19.11.2002	14.03.2003	Kayseri	Province	Turkish	2014
Turkey	Recep Tayyip Erdoğan	14.03.2003	in office[d]	Istanbul	Province	Turkish	2014
Uganda	Apollo Milton Obote	09.10.1962	25.01.1971	Apac	District (2004)	Langi	2002
Uganda	Idi Amin Dada Oumee	25.01.1971	11.04.1979	Arua	District (2004)	Kakwa	2002
Uganda	Yusuf Kironde Lule	13.04.1979	20.06.1979	n/a	District (2004)	Baganda	2002
Uganda	Godfrey Lukongwa Binaisa	20.06.1979	12.05.1980	n/a	District (2004)	Baganda	2002
Uganda	Paulo Muwanga	18.05.1980	17.12.1980	n/a	District (2004)	Baganda	2002
Uganda	Apollo Milton Obote	17.12.1980	27.07.1985	Apac	District (2004)	Langi	2002
Uganda	Bazilio Olara-Okello	29.07.1985	29.01.1986	n/a	District (2004)	Acholi	2002
Uganda	Yoweri Kaguta Museveni	29.01.1986	in office[d]	Mbarara	District (2004)	Banyakole	2002
Venezuela	Rómulo Betancourt	13.02.1959	11.03.1964	Miranda	State		
Venezuela	Raúl Leoni Otero	11.03.1964	11.03.1969	Bolívar	State		
Venezuela	Rafael Caldera	11.03.1969	12.03.1974	Yaracuy	State		
Venezuela	Carlos Andrés Pérez	12.03.1974	12.03.1979	Táchira	State		
Venezuela	Luis Herrera Campins	12.03.1979	02.02.1984	Portuguesa	State		
Venezuela	Jaime Ramón Lusinchi	02.02.1984	02.02.1989	Anzoátegui	State		
Venezuela	Carlos Andrés Pérez	02.02.1989	31.08.1993	Táchira	State		
Venezuela	Ramón José Velásquez	31.08.1993	02.02.1994	Táchira	State		
Venezuela	Rafael Caldera	02.02.1994	02.02.1999	Yaracuy	State		
Venezuela	Hugo Chávez	02.02.1999	05.03.2012	Barinas	State		
Venezuela	Nicolás Maduro Moros	05.03.2012	in office[d]	Distrito Capital	State		
Vietnam	Lê Duẩn	03.09.1969	10.07.1986	Quang Tri	Province	Kinh	1999
Vietnam	Trường Chinh	10.07.1986	18.12.1986	Nam Dinh	Province	Kinh	1999
Vietnam	Nguyễn Văn Linh	18.12.1986	27.06.1991	Hung Yen	Province	Kinh	1999
Vietnam	Đỗ Mười	27.06.1991	29.12.1997	Ha Noi	Province	Kinh	1999
Vietnam	Lê Khả Phiêu	29.12.1997	22.04.2001	Thanh Hoa	Province	Kinh	1999
Vietnam	Nông Đức Mạnh	23.04.2001	19.01.2011	Bac Kan	Province	Tay	1999
Vietnam	Nguyễn Phú Trọng	19.01.2011	in office[d]	Ha Noi	Province	Kinh	1999

Notes: The table shows political leaders along with birth regions and ethnic groups. Entries marked with an asterisk are leaders born outside the current boundaries of the respective country. In several countries, Federal Districts and Union Territories are treated as conventional ADM1 regions (e.g., states). To facilitate the generation of disaster-area fixed effects and zonal statistics for control variables, ADM1 definitions are held constant over time and EM-DAT locations are matched to the ADM1 definition valid at a given reference year ("reference point"). The column "ADM1 reference point" shows the ADM1 unit selected for each country along with the reference year in parenthesis. If no year is provided, the reference year is 2017. Eritrea was not considered to be part of Ethiopia given Ethiopia's lack of control over most of Eritrea's territory during the study period. Due to special features of shapefiles necessary for the creation of control variables, the number of districts (ADM1) in Malawi is slightly higher than the official number, without implications for the coding of birth regions. We match leader ethnicities to census or survey data. While disasters are unlikely to significantly influence the ethnic composition of ADM1 regions, we make use of the most recent census/survey before a disaster where multiple years are indicated (column "census year(s)") in order to further alleviate endogeneity concerns. In India, ethnicity data are unavailable for Union Territories (except for Delhi). In Pakistan, ethnic groups are imputed (based on online search) for Azad Kashmir, F.A.T.A. and Northern Areas, as these provinces are not included in the census. In Bangladesh, Bengali Muslims were identified as anyone stating to be Muslim in the listed censuses, given that almost 100% of Bangladesh's population comprises ethnic Bengalis. In Bolivia, Chile, Honduras, Mexico, Nicaragua and Panama, Whites/Mestizos were identified as anyone who does not consider him/herself to be a member of an indigenous group (and, where applicable, who is not of African origin or indicates being native to an Asian or Middle Eastern country). In Peru, we distinguished indigenous groups from Whites/Mestizos based on language. In the Democratic Republic of Congo we combined Ethnic groups according to geographic characteristics, following DHS classifications (UIN = Ubangi and Itimbiri-Ngiri; KKT = Kasai-Katanga-Tanganika). In Ecuador, the definition of Mestizo includes Montubios. In India, we classified ethnic groups based on the intersection of religion and language, with the exception of Other Backward Castes, Scheduled Castes and Scheduled Tribes, which we treated as separate groups given their substantially lower social standing.

Further notes: [a] Exact birth location unavailable; we used high-school location instead. [b] Leader was likely born outside the current boundaries of the country but spent significant parts of childhood in indicated region. [c] Original entry from Archigos database corrected after cross-checking sources. [d] Leaders marked as still in office, were still in office on July 1st, 2018. [e] Archigos database extended with online search.

Table A2. Control variables by country

Country	Barren land (%)	# ports	# nuclear plants	Capital city (%)	Night light per 1000 people[a]	Population densitiy[b]	City population[b]	Ruggedness[c]
Afghanistan	35.4	0.0	0.0	10.0	1.3	0.3	360.6	3.7
	(15.6)	(0.0)	(0.0)		(1.8)	(1.0)	(923.0)	(2.0)
	[0.2,70.6]	[0.0,0.0]	[0.0,0.0]		[0.0,8.3]	[0.0,6.1]	[0.0,4720.9]	[0.1,8.6]
Angola	0.2	0.0	0.0	41.8	3.9	0.5	2516.7	0.8
	(0.4)	(0.0)	(0.0)		(2.6)	(1.3)	(2939.2)	(0.5)
	[0.0,2.2]	[0.0,0.0]	[0.0,0.0]		[0.2,11.8]	[0.0,6.5]	[0.0,10612.5]	[0.1,3.0]
Argentina	5.1	0.2	0.6	15.1	86.0	0.1	3740.0	0.6
	(7.4)	(0.4)	(0.8)		(48.6)	(0.4)	(5361.0)	(0.9)
	[0.0,36.6]	[0.0,1.0]	[0.0,3.0]		[19.9,267.2]	[0.0,3.6]	[0.0,23860.4]	[0.1,5.9]
Bangladesh	0.3	0.0	0.0	38.1	2.4	1.3	6643.3	0.1
	(0.5)	(0.0)	(0.0)		(0.8)	(0.9)	(6882.6)	(0.2)
	[0.0,2.9]	[0.0,0.0]	[0.0,0.0]		[0.3,4.6]	[0.1,8.2]	[108.0,27684.1]	[0.0,1.3]
Bolivia	4.4	0.0	0.0	56.7	18.6	0.0	1811.9	1.2
	(8.0)	(0.0)	(0.0)		(8.0)	(0.1)	(1495.0)	(1.0)
	[0.0,55.6]	[0.0,0.0]	[0.0,0.0]		[5.4,52.5]	[0.0,0.5]	[0.0,4599.8]	[0.1,4.7]
Brazil	0.2	0.6	0.3	0.6	43.5	1.0	10548.3	0.5
	(0.3)	(0.7)	(0.7)		(17.8)	(2.1)	(12518.2)	(0.4)
	[0.0,2.7]	[0.0,3.0]	[0.0,2.0]		[7.7,75.2]	[0.0,8.4]	[89.4,59021.8]	[0.0,2.9]
Chile	16.4	0.0	0.0	36.4	69.3	0.2	2628.6	2.8
	(21.7)	(0.0)	(0.0)		(71.8)	(0.5)	(3112.3)	(1.0)
	[0.0,78.6]	[0.0,0.0]	[0.0,0.0]		[14.4,429.9]	[0.0,2.0]	[0.0,9115.4]	[1.0,7.1]
China	8.1	0.1	1.4	2.4	13.0	0.3	32861.2	2.3
	(19.4)	(0.4)	(3.4)		(9.4)	(0.4)	(50198.6)	(1.2)
	[0.0,88.1]	[0.0,4.0]	[0.0,22.0]		[2.2,70.5]	[0.0,5.9]	[0.0,481157.6]	[0.0,7.7]
Colombia	0.3	0.0	0.0	16.1	24.5	0.6	3754.1	1.7
	(0.5)	(0.0)	(0.0)		(13.1)	(1.6)	(6210.2)	(1.0)
	[0.0,4.7]	[0.0,0.0]	[0.0,0.0]		[0.9,74.7]	[0.0,7.4]	[0.0,23161.7]	[0.0,5.5]
Costa Rica	0.0	0.0	0.0	40.0	59.5	0.1	467.8	2.4
	(0.0)	(0.0)	(0.0)		(11.2)	(0.1)	(540.2)	(0.8)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[39.4,84.8]	[0.0,0.3]	[0.0,1760.0]	[1.0,4.3]
Cuba	0.0	1.8	0.0	22.4	22.0	0.4	707.1	0.8
	(0.0)	(1.6)	(0.0)		(10.3)	(1.3)	(957.4)	(0.5)
	[0.0,0.3]	[0.0,6.0]	[0.0,0.0]		[3.7,72.7]	[0.0,8.7]	[0.0,2913.0]	[0.0,2.3]
DR Congo	0.0	0.0	0.0	12.7	1.2	1.5	1493.2	0.7
	(0.0)	(0.0)	(0.0)		(3.0)	(4.3)	(2910.7)	(0.6)
	[0.0,0.1]	[0.0,0.0]	[0.0,0.0]		[0.0,29.6]	[0.0,21.5]	[0.0,16086.6]	[0.0,2.2]
Dominican Rep.	0.0	0.0	0.0	31.6	21.8	0.5	1024.7	1.6
	(0.0)	(0.0)	(0.0)		(4.9)	(0.6)	(1244.1)	(0.6)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[11.4,46.0]	[0.1,2.8]	[0.0,3491.1]	[0.2,3.6]
Ecuador	2.2	0.0	0.0	23.4	40.9	0.2	931.7	1.7
	(10.1)	(0.0)	(0.0)		(56.5)	(0.2)	(1312.0)	(1.1)
	[0.0,56.9]	[0.0,0.0]	[0.0,0.0]		[1.5,4955.8]	[0.0,0.6]	[0.0,4520.7]	[0.1,4.4]
El Salvador	0.0	0.0	0.0	59.5	21.2	0.9	602.9	1.8
	(0.0)	(0.0)	(0.0)		(3.4)	(1.4)	(520.8)	(0.4)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[12.2,26.9]	[0.2,5.9]	[0.0,1096.5]	[1.2,3.7]
Ethiopia	8.0	0.0	0.0	10.2	0.7	0.3	400.9	1.5
	(15.5)	(0.0)	(0.0)		(1.2)	(1.3)	(820.0)	(1.1)
	[0.0,57.1]	[0.0,0.0]	[0.0,0.0]		[0.0,6.3]	[0.0,7.2]	[0.0,3317.9]	[0.1,6.2]
Greece	0.2	0.3	0.0	18.8	136.9	1.4	960.2	3.0
	(1.2)	(0.4)	(0.0)		(58.0)	(4.1)	(1446.1)	(1.3)
	[0.0,9.7]	[0.0,1.0]	[0.0,0.0]		[5.4,245.8]	[0.0,16.6]	[0.0,3981.7]	[0.6,6.0]
Guatemala	0.0	0.0	0.0	33.8	13.4	0.7	737.2	2.1
	(0.0)	(0.0)	(0.0)		(6.9)	(1.5)	(1078.4)	(1.1)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[0.9,41.3]	[0.0,7.1]	[0.0,2738.3]	[0.1,5.0]
Haiti	0.0	0.0	0.0	51.6	1.2	0.8	982.3	2.5
	(0.0)	(0.0)	(0.0)		(0.9)	(1.0)	(1062.7)	(0.6)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[0.0,3.8]	[0.1,3.7]	[0.0,2642.8]	[1.1,4.4]
Honduras	0.0	0.0	0.0	33.3	17.5	0.2	551.5	2.1
	(0.0)	(0.0)	(0.0)		(8.4)	(0.3)	(613.0)	(0.9)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[2.1,51.6]	[0.0,0.8]	[0.0,2069.0]	[0.4,4.8]
India	2.6	0.3	1.2	6.0	9.8	1.3	17358.1	1.3
	(5.3)	(0.5)	(2.3)		(18.2)	(4.0)	(21380.6)	(1.8)
	[0.0,34.2]	[0.0,3.0]	[0.0,17.0]		[0.5,414.0]	[0.0,50.3]	[0.0,159538.5]	[0.0,8.3]
Indonesia	0.0	0.3	0.0	9.2	6.5	1.0	3451.8	1.3
	(0.0)	(0.5)	(0.0)		(5.7)	(2.7)	(5762.2)	(0.7)
	[0.0,0.0]	[0.0,2.0]	[0.0,0.0]		[0.0,84.5]	[0.0,16.7]	[0.0,34596.4]	[0.1,3.3]
Iran	50.7	0.0	0.0	4.4	114.6	0.1	1069.2	3.1
	(37.5)	(0.0)	(0.0)		(245.5)	(0.1)	(1782.3)	(1.8)
	[0.0,100.0]	[0.0,0.0]	[0.0,0.0]		[20.4,3071.1]	[0.0,0.8]	[0.0,14678.0]	[0.1,9.6]
Kenya	6.7	0.0	0.0	15.9	1.3	0.3	1140.6	0.8
	(10.6)	(0.0)	(0.0)		(1.2)	(0.8)	(1517.9)	(0.8)
	[0.0,38.7]	[0.0,0.0]	[0.0,0.0]		[0.1,7.2]	[0.0,5.8]	[0.0,6205.0]	[0.1,3.6]
Madagascar	0.0	0.0	0.0	39.3	0.6	0.0	819.1	1.2
	(0.0)	(0.0)	(0.0)		(0.3)	(0.0)	(1036.3)	(0.2)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[0.0,1.8]	[0.0,0.1]	[0.0,3396.6]	[0.5,1.8]
Malawi	0.0	0.0	0.0	17.5	1.4	0.2	237.0	1.1
	(0.0)	(0.0)	(0.0)		(0.4)	(0.1)	(468.5)	(0.5)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[0.5,2.3]	[0.1,0.4]	[0.0,1652.5]	[0.4,3.3]
Malaysia	0.0	0.4	0.0	11.7	34.5	0.6	1183.4	0.9
	(0.0)	(0.6)	(0.0)		(14.7)	(1.1)	(1458.0)	(0.5)

	[0.0,0.0]	[0.0,2.0]	[0.0,0.0]		[3.2,57.5]	[0.0,4.3]	[0.0,8094.1]	[0.1,2.0]
Mexico	0.0	0.0	0.4	5.8	59.7	0.4	4188.2	2.0
	(0.1)	(0.0)	(0.8)		(25.0)	(1.5)	(6208.3)	(1.1)
	[0.0,0.6]	[0.0,0.0]	[0.0,2.0]		[6.9,123.5]	[0.0,11.2]	[0.0,60164.3]	[0.0,5.1]
Mozambique	0.0	0.0	0.0	34.3	2.3	0.2	1147.5	0.5
	(0.0)	(0.0)	(0.0)		(3.6)	(0.5)	(1045.3)	(0.2)
	[0.0,0.1]	[0.0,0.0]	[0.0,0.0]		[0.0,22.1]	[0.0,3.0]	[0.0,3897.9]	[0.0,1.1]
Myanmar	0.0	0.0	0.0	5.5	2.7	0.1	950.5	1.7
	(0.0)	(0.0)	(0.0)		(2.4)	(0.2)	(1677.5)	(0.8)
	[0.0,0.1]	[0.0,0.0]	[0.0,0.0]		[0.1,15.0]	[0.0,0.9]	[0.0,6119.0]	[0.1,4.5]
Nepal	1.5	0.0	0.0	59.0	1.7	0.2	549.9	5.2
	(2.1)	(0.0)	(0.0)		(0.8)	(0.1)	(524.5)	(1.2)
	[0.2,12.2]	[0.0,0.0]	[0.0,0.0]		[0.0,3.3]	[0.0,0.4]	[0.0,1572.7]	[1.8,7.7]
Nicaragua	0.0	0.0	0.0	42.3	40.0	0.1	349.4	0.9
	(0.0)	(0.0)	(0.0)		(63.9)	(0.3)	(437.0)	(0.4)
	[0.0,0.0]	[0.0,0.0]	[0.0,0.0]		[0.5,231.2]	[0.0,1.7]	[0.0,1012.6]	[0.1,2.4]
Niger	47.4	0.0	0.0	34.4	2.2	0.1	411.2	0.2
	(27.3)	(0.0)	(0.0)		(2.1)	(0.5)	(511.0)	(0.1)
	[0.2,91.9]	[0.0,0.0]	[0.0,0.0]		[0.3,7.2]	[0.0,4.0]	[0.0,1536.0]	[0.0,0.5]
Nigeria	0.2	0.1	0.0	1.9	4.7	1.1	3870.6	0.3
	(0.3)	(0.3)	(0.0)		(8.2)	(3.9)	(5924.3)	(0.2)
	[0.0,1.8]	[0.0,1.0]	[0.0,0.0]		[0.2,58.7]	[0.1,36.6]	[0.0,32142.3]	[0.0,1.1]
Pakistan	31.4	0.0	0.6	3.2	10.8	1.1	9128.8	2.6
	(26.4)	(0.0)	(0.8)		(5.9)	(2.2)	(10789.9)	(2.8)
	[0.0,98.5]	[0.0,0.0]	[0.0,4.0]		[0.0,27.5]	[0.0,8.5]	[0.0,45977.1]	[0.0,9.5]
Panama	0.4	0.0	0.0	43.5	19.6	0.1	493.1	1.6
	(0.5)	(0.0)	(0.0)		(7.6)	(0.2)	(622.8)	(0.7)
	[0.0,2.1]	[0.0,0.0]	[0.0,0.0]		[4.1,34.2]	[0.0,0.6]	[0.0,1673.1]	[0.6,3.3]
Papua N. Guinea	0.0	0.0	0.0	3.7	0.5	0.9	12.3	1.9
	(0.0)	(0.0)	(0.0)		(0.5)	(2.2)	(63.2)	(0.8)
	[0.0,0.2]	[0.0,0.0]	[0.0,0.0]		[0.0,2.1]	[0.0,11.1]	[0.0,338.1]	[0.5,3.4]
Peru	12.1	0.0	0.0	22.1	19.0	0.1	2204.8	2.1
	(15.5)	(0.0)	(0.0)		(9.0)	(0.4)	(3776.2)	(1.0)
	[0.0,63.7]	[0.0,0.0]	[0.0,0.0]		[3.1,57.1]	[0.0,3.2]	[0.0,13830.8]	[0.0,4.6]
Philippines	0.0	0.3	0.0	19.8	4.1	1.1	3684.9	1.9
	(0.0)	(0.5)	(0.0)		(1.9)	(3.8)	(5375.3)	(0.6)
	[0.0,0.0]	[0.0,2.0]	[0.0,0.0]		[0.3,10.3]	[0.0,22.8]	[0.0,25231.8]	[0.1,5.1]
Romania	0.1	0.0	0.4	43.4	85.7	0.3	1085.0	1.2
	(0.2)	(0.0)	(0.7)		(17.3)	(1.0)	(1063.3)	(0.6)
	[0.0,1.3]	[0.0,0.0]	[0.0,2.0]		[12.3,136.2]	[0.0,7.4]	[0.0,2865.0]	[0.1,3.6]
South Africa	0.3	0.7	0.4	19.0	39.1	0.4	3871.5	2.4
	(0.9)	(0.5)	(0.8)		(15.4)	(0.6)	(3889.8)	(0.9)
	[0.0,6.6]	[0.0,2.0]	[0.0,2.0]		[10.2,85.4]	[0.0,2.8]	[0.0,17145.7]	[0.3,4.6]
Sri Lanka	0.1	0.0	0.0	47.9	14.2	0.6	287.4	0.7
	(0.2)	(0.0)	(0.0)		(3.2)	(0.7)	(302.2)	(0.5)
	[0.0,1.9]	[0.0,0.0]	[0.0,0.0]		[3.1,19.8]	[0.1,3.6]	[0.0,638.9]	[0.0,2.7]
Sudan	35.3	0.0	0.0	33.3	4.6	0.0	1583.8	0.4
	(32.3)	(0.0)	(0.0)		(5.8)	(0.1)	(2200.4)	(0.3)
	[0.0,99.5]	[0.0,0.0]	[0.0,0.0]		[0.0,34.1]	[0.0,0.3]	[0.0,7696.1]	[0.0,1.5]
Tajikistan	23.0	0.0	0.0	26.3	16.3	0.5	275.1	4.1
	(17.9)	(0.0)	(0.0)		(12.2)	(1.2)	(342.6)	(2.4)
	[0.4,66.9]	[0.0,0.0]	[0.0,0.0]		[0.0,68.5]	[0.0,4.0]	[0.0,832.0]	[0.8,9.3]
Tanzania	0.0	0.0	0.0	21.4	1.6	0.4	862.7	0.6
	(0.1)	(0.0)	(0.0)		(1.8)	(0.8)	(1597.7)	(0.4)
	[0.0,0.9]	[0.0,0.0]	[0.0,0.0]		[0.0,6.8]	[0.0,3.0]	[0.0,6933.2]	[0.0,1.8]
Thailand	0.0	0.1	0.0	6.1	24.3	0.3	1154.4	1.2
	(0.0)	(0.2)	(0.0)		(10.5)	(0.7)	(1932.0)	(0.6)
	[0.0,0.1]	[0.0,1.0]	[0.0,0.0]		[4.1,81.0]	[0.0,3.7]	[0.0,9905.9]	[0.0,2.9]
Turkey	0.5	0.3	0.0	9.1	53.9	0.3	2326.3	2.8
	(0.7)	(0.6)	(0.0)		(52.3)	(0.6)	(5007.4)	(1.2)
	[0.0,3.4]	[0.0,3.0]	[0.0,0.0]		[10.1,530.0]	[0.0,3.0]	[0.0,27598.2]	[0.5,6.0]
Uganda	0.3	0.0	0.0	14.8	0.4	0.8	270.5	1.2
	(0.9)	(0.0)	(0.0)		(0.8)	(2.2)	(667.9)	(0.7)
	[0.0,5.4]	[0.0,0.0]	[0.0,0.0]		[0.0,4.1]	[0.0,11.0]	[0.0,2577.0]	[0.2,3.9]
Venezuela	0.0	0.1	0.0	43.6	57.6	0.2	2891.9	1.5
	(0.1)	(0.3)	(0.0)		(28.4)	(0.3)	(3106.4)	(1.1)
	[0.0,0.2]	[0.0,1.0]	[0.0,0.0]		[15.3,139.9]	[0.0,1.4]	[0.0,12165.8]	[0.0,4.2]
Vietnam	0.1	0.0	0.0	9.0	6.2	0.4	778.3	2.2
	(0.1)	(0.0)	(0.0)		(2.5)	(0.8)	(1696.0)	(1.2)
	[0.0,0.6]	[0.0,0.0]	[0.0,0.0]		[0.5,14.3]	[0.0,9.3]	[0.0,11118.1]	[0.0,6.1]
Full sample	6.2	0.1	0.3	16.9	21.0	0.6	7627.2	1.7
	(17.2)	(0.4)	(1.5)		(51.6)	(2.2)	(21659.8)	(1.5)
	[0.0,100.0]	[0.0,6.0]	[0.0,22.0]		[0.0,3071.1]	[0.0,50.3]	[0.0,481157.6]	[0.0,9.6]

Notes: The table displays means, (standard deviations) and [min,max] for all control variables used in the analysis. For the binary indicator "Capital city" only percentages are reported. [a] Raw night light intensity values can reach a maximum of 63. Night light intensity per 1,000 people was calculated by first aggregating night light emissions across grid cells within each ADM region and by dividing by the population (times 1,000) living in the respective area. Afterwards, for each disaster, area-weighted averages were created. [b] For readability purposes, population density is scaled in terms of 1,000 people per km^2 and city population is scaled in terms of thousands of inhabitants. [c] Ruggedness is scaled in terms of 100s of meters of elevation differences.