Population displacement and urban conflict: Global evidence from more than 3300 flood events

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Population displacement and urban conflict: Global evidence from more than 3300 flood events

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Abstract:

In this paper, we study the effect of displacement of population into cities on urban conflict in developing countries. To do so, we construct a novel measure of exposure to floods, using data on more than 3,300 flood events worldwide, as an exogenous source of population displacement. We combine this with city level observations of more than 9,000 urban social disorder events. Exposure to floods is found to be associated with higher likelihood and frequency of urban social disorder. Our evidence suggests that the effects of floods on urban disorder occur mainly through the displacement of population into large cities. Exploring the information on urban disorder events in more detail, we find that the association between city growth and urban disorder is strongest for events related to public service provision, wages and food prices.

Key words: climate change; floods; displacement; urbanization; conflict; social disorder

JEL Codes: O18, Q34, Q54, Q56, R23

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1. Introduction

Conflict is widely recognised as one of the most pressing issues hindering development prospects worldwide (Collier and Hoeffler 2004; Kalyvas 2006; Blattman and Miguel 2010; World Bank 2011; Bruck et al 2016; Bircan et al. 2017; Harari and La Ferrara 2018; McGuirk and Nunn 2020). Moreover, as developing countries urbanise, conflict has increasingly moved from rural to urban areas; unlike most other forms of conflict, the rate of urban social disorder events, including demonstrations and riots, has increased steadily over recent decades (Bahgat et al. 2018). In this paper, we study the effect of population displacement due to floods on urban conflict. To do so, we construct a novel measure of exposure to floods, using data on more than 3,300 flood events worldwide from 1985-2015, as an exogenous source of population displacement. We combine this with city level observations of more than 9,000 urban social disorder events that occurred in large cities in developing countries.

Disasters, weather shocks and deteriorating climatic conditions increasingly represent an important factor displacing population from rural to urban areas, and have become a relevant driver behind current urbanisation and city growth in developing countries (Barrios et al. 2006, Henderson et al. 2017, Castells-Quintana et al. 2021). Floods, in particular, displace tens of millions of people from their homes every year (Brakenridge 1985–present). The risk of flooding is also anticipated to increase substantially in the coming decades, due to a combination of increased exposure—as a result of trends such as population and economic growth—and rising hazard, as climate change alters rainfall patterns and causes sea levels to rise (IPCC 2014). In spite of their large scale, and the threat of greater future risks, the social and economic consequences of these disruptions remains poorly understood.

Some of the main challenges of disorderly displacement into cities in response to natural disasters, like floods, are expected to be disruptions to economic activity and social disorder in urban areas (for recent reviews, see Waldinger, 2016, and Castells-Quintana et al, 2018). There are indeed sound reasons to expect that the displacement of people into cities leads to higher social tensions there. For instance, when governments do not respond to the arrival of new population in cities due to displacement, we may expect protests and riots associated with the (lack of) provision of public services, employment opportunities, wages and prices. However, empirical evidence of the effects of rural-urban displacement on social disorder in urban areas remains limited. In fact, population displacement, and the potential for social disorder as a consequence, is regularly cited as one of the most important omitted impacts of climate change in the climate-economics literature (see e.g. Stern 2013, Revesz et al. 2014, Sterner 2015). The aim of this paper is precisely to analyse the potential effects that displacement into large cities, due to flooding, can have on urban social disorder.

Existing literature on the link between city growth and urban conflict has found inconclusive results (e.g. Buhaug and Urdal 2013; Ostby 2016). Establishing the effects of city growth on urban conflict faces two main challenges. First, not all urbanization is equal. Where cities are growing due to economic expansion and increasing economic opportunities, it is less likely that the arrival of new workers will create social tensions. On the other hand, if cities are growing in an unplanned way, in particular as a result of population displacement elsewhere in the country, this might be more likely to create social tensions. Secondly, there is the methodological issue of the need to identify exogenous sources of variation in urban population growth or in rates of inflows from rural to urban areas.

To overcome these challenges, we exploit exogenous variation in population exposure to flooding. Specifically, we combine high resolution population grids with shapefiles of the areas affected by more than 3,000 flood events worldwide, to generate a time-varying, population and distance weighted measure of flood exposure. We use this exogenous variation in flood exposure to disentangle different types of city growth and to estimate the causal effect of population displacement on social disorder in cities. Further, we review in detail the descriptive information on each of the events included in the Urban Social Disorder dataset, and complement this with additional data sources (e.g. newspaper reports), to explore the type of disorder events most strongly associated with population displacement into cities.

Our paper relates to at least three strands in the literature: i) papers studying the connection between climate and conflict (e.g. Miguel et al. 2004, Hendrix and Salehyan 2012; Mach et al. 2019; McGuirk and Nunn 2020), ii) papers studying the connection between weather shocks, population displacements and city growth (e.g. Rajan and Bhagat 2019; Peri and Sasahara 2019; Castells-Quintana et al. 2021), and iii) papers focusing on population pressure and conflict (e.g. Buhaug and Urdal 2013, Ostby 2016, Acemoglu et al. 2020). In Section 2 we provide a brief overview of the related literature. While the literature suggests a potential connection between climate, population displacement into cities and conflict in urban areas, to the best of our knowledge, there is no paper empirically testing this connection in a global panel of countries and/or cities. Our paper aims to fill this gap.

Our findings indicate that flooding elsewhere in the country leads to increased likelihood and frequency of urban social disorders in large cities. And we find strong evidence that the effect of floods on urban disorder happens mainly due to flooding acting as a "push" factor, increasing city size by displacing population to cities. Moreover, relying on a system of recursive equations, we separate out city growth that is driven by push factors, including floods, versus city growth that is responding to the pull of economic opportunity. We show dramatically contrasting results of these two different types of city growth, with push-driven city growth significantly increasing the probability and count of urban disorders. Finally, we also find suggestive evidence that the effect of city growth on urban conflict primarily relates to protests and riots in response to a lack of public service provision, low wages and increasing food prices.

The remainder of our paper proceeds as follows: In Section 2, we briefly review three strands of related literature. In Section 3, we present our data, providing a descriptive analysis of the coevolution of floods, city growth, and social disorder in urban areas. Section 4 describes the econometric analysis and presents our main results: in Section 4.1 looking at displacement and urbans disorders, in Section 4.2 studying the role of city growth, and in Section 4.3 analysing results be event type. Finally, Section 5 concludes.

2. Climate, Displacement into large cities, and Conflict in Urban Areas: A Review of the Literature

Changes in climatic patterns, weather shocks and natural disasters can all cause huge displacements of population (Henderson et al. 2014, 2017). As mentioned in Section 1, floods alone have displaced 650 million people worldwide in the past 30 years. In contrast to other types of weather shocks, such as changes in rainfall and temperature patterns, flooding forces people to move in a more direct way, as their homes become uninhabitable, at least in the short run. When floods occur outside urban areas, it is likely that many of the displaced population end up in cities (Barrios et al 2006). Large urban areas are likely to be a main destination. This (somehow unexpected) displacement of population into large cities creates unplanned city growth, and there are reasons to expect that this leads to increased social disorders in cities. In this section, and before we move to empirical analysis, we explain how people displaced by weather shocks and natural disasters, like flooding, can increase social disorder in cities. We do this relying on theoretical insights in the literature and on related empirical evidence to date.

Climate, conflict and urban social disorders:

Changes in climatic patterns, weather shocks and natural disasters have been shown to be associated with increased conflict in many countries. Climate change can affect the economic opportunities of different groups within societies, and trigger conflict over natural resources and distribution of power. In this spirit, several papers have studied the relationship between climatic variables, income shocks, and nation-wide conflict (see for instance Mach et al 2019; Miguel et al. 2004, Ciccone 2011, 2013, Maystadt and Ecker 2014, Hendrix and Salehyan 2012, and Couttenier and Soubeyran 2014, for countries in Sub-Saharan Africa, or Bohlken and Sergenti 2010, for states in India). These papers have usually relied on the consensus that low levels of income are correlated with high levels of uprisings, protests and riots. As income is endogenous to conflict, climatic shocks have been used for identification. Changes in rainfall patterns, in particular, have been used as a source of exogenous variation of income.

In terms of the mechanisms that relate climatic disruptions with conflict, the literature has suggested at least five different mechanisms.[1] A first body of literature focuses on access to public goods in rural areas, such as water or scarcity of renewable resources. During rainfall shortages water stores decline, and consumers may come into conflict within their own society over access to wells and riverbeds (Kahl 2006) or over water rights and access (Eriksen and Lind 2009). Hauge and Ellingsen (1998) shows that factors like deforestation, land degradation and scarce supply of freshwater, alone and in combination with high population density, increases the risk of armed conflict. A second group of authors focuses on the effect of droughts and floods on food prices, leading to disputes between rural producers and urban consumers. Alexandratos (2008), for example, has shown that the rising price of staples crops in 2008 and 2011 led to massive protests and riots when urban consumers started to demand relief from food price inflation. A third mechanism relates directly to the effect on government revenues through a reduction of the tax base, or an increase in the demand for services and assistance to respond to weather shocks in the rural areas. This is particularly true in countries where agriculture and other water-intensive sectors are central for the national economy. A fourth mechanism relates to the effects on overall economic growth (i.e., Miguel et al 2004, Barrios et al 2010, Jensen and Gleditsch 2009). Rainfall anomalies can lead to crop failure, which at the same time affect economic productivity. General economic discontent may in turn lead to public disorder and conflict. In what we have identified as a fifth mechanism, climatic disruptions may also affect rural livelihoods, displacing people to urban areas and fuelling unplanned city growth. This translates into an excess of demand of public goods,

[1] The literature has usually focused on rainfall, and in particular extreme events, since deviations from normal rainfall disrupt the expectations societies develop about normal rainfall patterns, and accordingly, their plans for crops and coping strategies (Reardon and Taylor, 1996).

which can increase social tensions, and potentially conflict, in cities (Hendrix and Salehyan, 2012). To the best of our knowledge, this connection between climate disruptions and conflict has not been explicitly tested in the literature to date.

Climate, displaced population and unplanned city growth:

The literature has already shown how weather shocks can foster unplanned urbanisation and city growth. For example, Barrios et al (2006) show how shortages in rainfall have increased urbanization in Sub-Saharan African (SSA) countries (although not in the rest of the developing world). Bruckner (2012) finds similar results. Henderson et al. (2014, 2017) confirm the link between weather shocks and urbanization or city growth in SSA. Cattaneo and Peri (2016) and Castells-Quintana et al. (2021) show that this happens globally, with climate change altering the spatial distribution of population, including rural-urban migration and the growth of cities. According to this literature, more severe and persistent climate change will likely increase the challenges faced in rural areas and further accelerate migration to cities. Unplanned city growth in developing countries has already been highlighted as a main challenge for sustainable development (see UN 2018). As noted in Section 1, developing countries are experiencing a very fast process of urbanisation with large cities growing rapidly in size. Climate change, by disrupting climatic patterns and increasing the frequency and intensity of weather shocks and natural disasters, has become one major cause of rural-urban displacement of population in many developing countries (e.g. Rajan and Bhagat 2019; Peri and Sasahara 2019; Castells-Quintana et al. 2021). However, as noted, the empirical evidence to date has focused on rainfall and temperature anomalies, without paying much attention to other events. In this paper, we focus on floods as a cause of displacement of population and therefore as a potential driver of unplanned city growth.

Unplanned city growth and urban social disorder

Unplanned urbanization, due to displacement, can have important consequences in the lifestyle of city dwellers. In the absence of a sound response, this creates important frictions between migrants, locals and governments, all potentially leading to manifestations, riots and protests in those cities.

The literature that links migration and conflict has focused mainly on rural–urban migration as a potential driver of grievances and opportunities for violent mobilization (Urdal, 2005) or the relationship between population pressure and international conflict (Tir and Diehl, 1998). The explanations that the literature has used include relative deprivation and radicalization of migrants, reduced opportunity costs, enhanced social communication, and ethnic frictions. The influx of rural–urban migrants tends not to be accommodated by public or private sectors, and migrants are likely to experience rising relative deprivation, which in turn increases the likelihood of their engaging in social disorder (Gizewski and Homer-Dixon 1995).[2]

The displacement of population into cities can affect labour markets, food prices and public services demands. First, the displacement of population from rural to urban areas increases the supply of labour, especially low skilled, leading to more intense competition over jobs and putting a downward pressure on wages (Reuveny 2007). Second, the displacement of population into cities leads to an increase in the demand for basic public services, including housing[3] and other basic services such as sanitation, electricity, transportation, police protection and roads (Neuwirth 2005). If the supply of these services does not increase accordingly, competition and potential social frictions may arise. This can in turn undermine the state's ability to cope with the demands of an unplanned growing urban population, accentuating grievances and facilitating the rise in urban social disorders. This can be particularly strong when the tax base to collect government revenues is affected by weather shocks in the rural areas, or in economies where agriculture is still a central economic sector. Third, migration into cities can lead to an increase in food prices due to a combination of an increase in the demand for food in cities and a decrease in the supply due precisely to climatic disruptions in rural areas. Higher food price increases worsen living conditions,

[2] Migrants may also have problems adjusting to life in the cities, in particular because of disruption to their old customs and habits. As a result, migrants may tend to be more easily recruited into radical movements (Gizewski and Homer-Dixon 1995). Cities can also be ethnically and religiously diverse, and this mixing may represent a further destabilizing factor (Beall et al 2010).

[3] Depetris-Chauvin and Santos (2018) study the causal impact of internally displaced people inflows on rental prices in Colombia and find that these inflows cause excess of housing demand, an increase in rental prices and a decrease of real wages in the construction sector.

underlining grievances and potentially driving the rise of urban social disorders. The negative shock on low skill wages and the increase of food prices and the demands on the state will increase the opportunities for challenges to the state and the grievances of the population, in particular in weak states, leading to more frequent and intense urban social disorders and violence.

Despite the several theoretical reasons to expect a link between fast city growth and conflict in urban areas, there is a relatively limited literature that has empirically tested the link between the two. Buhaug and Urdal (2013) find no support for the "urbanization bomb"—the idea that urban population growth should lead to an increase in political violence in 55 major cities in Asia and SSA since 1960. Instead, they find that urban disorder is associated with lack of strong political institutions, economic shocks and ongoing civil conflict. However, Ostby (2016) investigates the relationship between migration into cities and political violence with city-level data in Africa and Asia, and finds that the movement of rural people into the cities creates social disorder through mechanisms such as poverty, unequal educational opportunities, and the socioeconomic marginalization of rural–urban migrants. Similarly, Bhavnani and Lacina (2015) show a causal effect of migration on social disorder in Indian states, using abnormal rainfall in migrant-sending states as an instrument for migration.

Recently, Acemoglu et al. (2020) have shown a causal effect of large population increases on internal violent conflicts. They consider a *Malthusian* channel: a larger population increases resource scarcity and encourages fighting over these scarce resources. They highlight that the main problem is not higher population itself, but increase in population that is not accompanied by increases in productivity or physical and human capital investments. They find that these effects are significantly larger in economies that experienced other sources of economic hardship (slower growth or droughts). We follow Acemoglu et al. (2020) by testing the effect of population pressure on conflict, in our case using flooding as an exogenous source of unplanned city growth.

3. Data and Descriptive Analysis

To study the effects of floods on social disorder in urban areas, we build a large and unique dataset, comprised of a panel of cities in developing countries, combining information on urban social disorder events at the city level, with information on floods occurring elsewhere in the country. Given our focus on the displacement of population into these large cities as the mechanism linking floods with urban social disorder, we also include in our dataset city-level population data from the UN. The urban social disorder (USD) data is observed for 103 cities in 89 countries over the period 1960-2014, while the floods archive that we draw on includes global coverage of flood events since 1985. Our main sample is therefore a panel of 103 cities observed over the period 1985-2015. In our main analysis, we aggregate the data to 5-year intervals, reflecting the constraint that we only observe city-level population data every 5 years.[4] Below we explain our key variables and sources. Table A.1 in Appendix A gives definitions and sources for main variables considered.

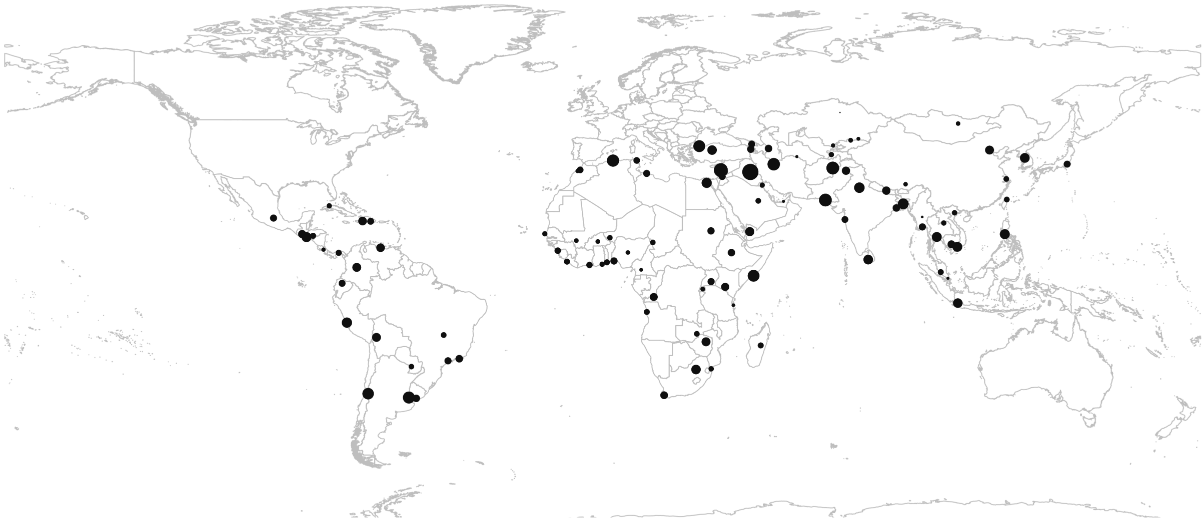
3.1 Data sources and main variables

Urban conflict data:

For conflict in urban areas, we use data from the Urban Social Disorder (USD) dataset v2.0 (Urdal and Hoelscher 2012, Bahgat et al. 2018).[5] This dataset contains information on social disorder events occurring in capitals and other major cities of the developing world over the period 1960-2014. Figure 1.A shows the locations of the 103 cities included in the USD data, reflecting the intensity of disorder events by city, while Figure 1.B shows the number of disorder events, and the estimated total number of participants in these events from the USD data, over time.

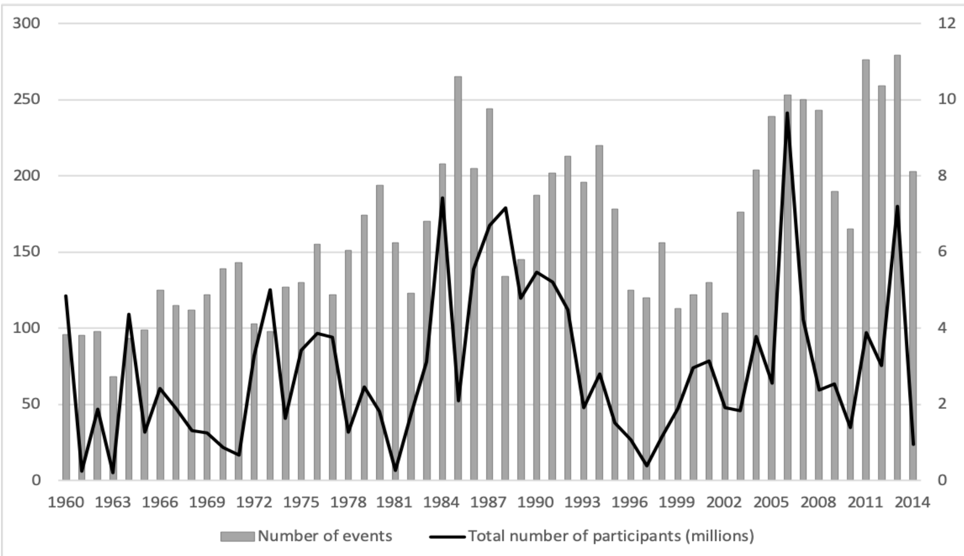
[4] The 5-year aggregation also reflects that it takes time to translate a flood shock into movement of people to social or economic tensions in urban areas. We checked that our main reduced-form results for the effect of displacement by flooding on urban social disorder hold when using annual variation in our data (results available on request).
[5] Available from https://www.prio.org/Data/Armed-Conflict/Urban-Social-Disorder/ (accessed November 2018).

Figure 1.A. Urban Social Disorder events



Note: Each black dot on the map represents one city included in the USD data. Dots are proportional to the total number of events for that city in the USD data.

Figure 1.B. Urban Social Disorder (USD) events and participants per year (in millions)



Note: The figure shows the number of social disorder events recorded per year (left hand axis) and the total number of participants in those events worldwide (right hand axis, in millions), according to data from the Urban Social Disorders v2.0 dataset. Participants, as estimated in the USD data, refers to the total number of active participants or people directly affected by the disorder events (the sum of 'actors' and 'targets', in the language of the USD data). Participant numbers presented in this figure are based on the *Participants_m* variable, which we construct by taking the mid-points of the intervals included in the USD data, and filling missing values with the median number of participants for events recorded in that city, as detailed in the main text.

The data comprise information extracted from electronic news reports in the Keesing's Record of World Events, for a range of social disorder events classified as either demonstrations, riots, or armed conflict (battles or terrorist events). There are over 9,000 individual events in the dataset, and each entry includes information on the location (city), timing, and type of event, the categories of actors involved, as well as estimates of the number of people involved in each incident and the number of fatalities (if any).

We code the information in the dataset, for integration with our floods and urban data, by aggregating over 5-year intervals, from 1985-2015, and construct measures of both intensive and extensive margins for disorder. To capture the extensive margin of disorder, we create a binary indicator for whether a given city experienced any disorder events in a 5-year period, which we label as *Pr(event)*. For the intensive margin, our primary measure is a count of the number of events per city-period, which we label as *N_Events*. We also construct measures based on estimated number of participants in each disorder event in the USD data. Participants, as estimated in the USD data, refers to the total number of active participants or people directly affected by the disorder events (the sum of 'actors' and 'targets', in the language of the USD data). The USD data include estimates of participant numbers for each event, coded into intervals.[6] To create a measure of participants, we take the mid-points of each of these intervals, and aggregate across events in a given city-period observation.[7] For a large proportion of the observations in the USD data, the number of participants is listed as "unknown" (39% of the sample). We create two different versions of the measure of participants; one labelled as *participants*, which excludes the events with "unknown" number of participants (treating these as zero); and another, labelled as *participants_m*, which fills values for these missing participant numbers based on the median number of

[6] The intervals are: Less than 10; 10-100; 101-1,000; 1,001-10,000; 10,001-100,000; 100,001-1,000,000; and over a million.
[7] For the "over a million" category we assign a value of 1,000,000. The USD data also include observations where the number of participants is coded as: "unknown but small" (18% of the sample), to which we assign a value of 10; "unknown but large" (8% of the sample), to which we assign a value of 1,000; "unknown but very large" (0.5% of the sample), to which we assign a value of 10,000.

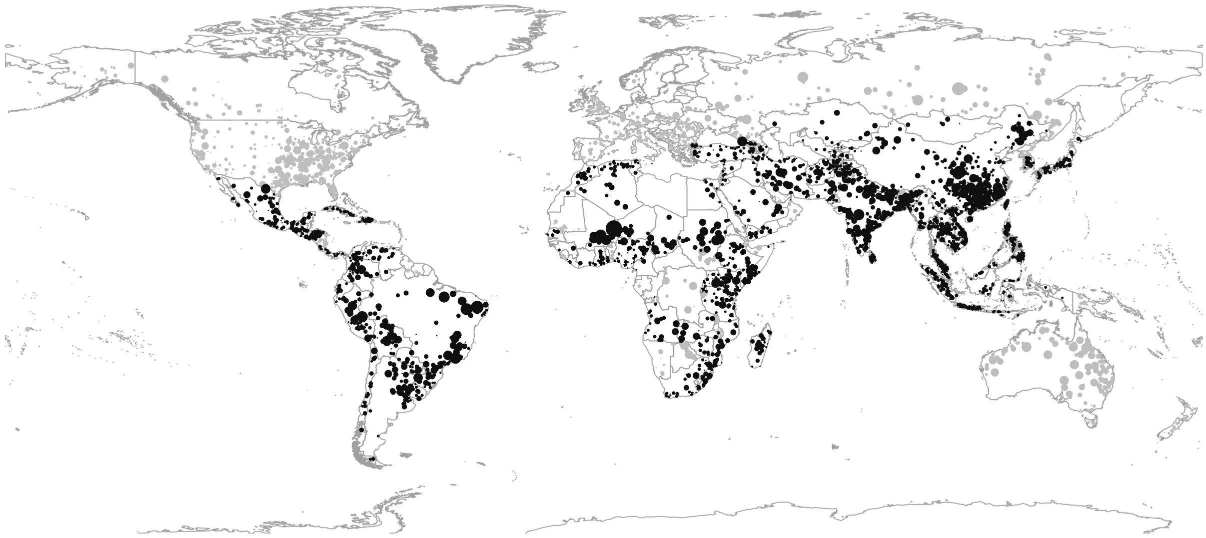
participants for events recorded in that city. We report results using both of these measures based on participant numbers, as robustness checks on our main findings.

Both the intensive and extensive measures are generated for all events, and separately for each of the three primary event type classifications included in the USD data; demonstrations, riots and armed conflict. There is also a description included with each entry in the data, extracted from the Keesing's report, which describes the cause of the incident. We thus look at each of these entries in the USD data to better understand the type of disorders that we observe in our sample of cities. This allows us to further classify disorders and explore heterogeneity in our results by motive of disorder (see Section 4.3).

Floods data

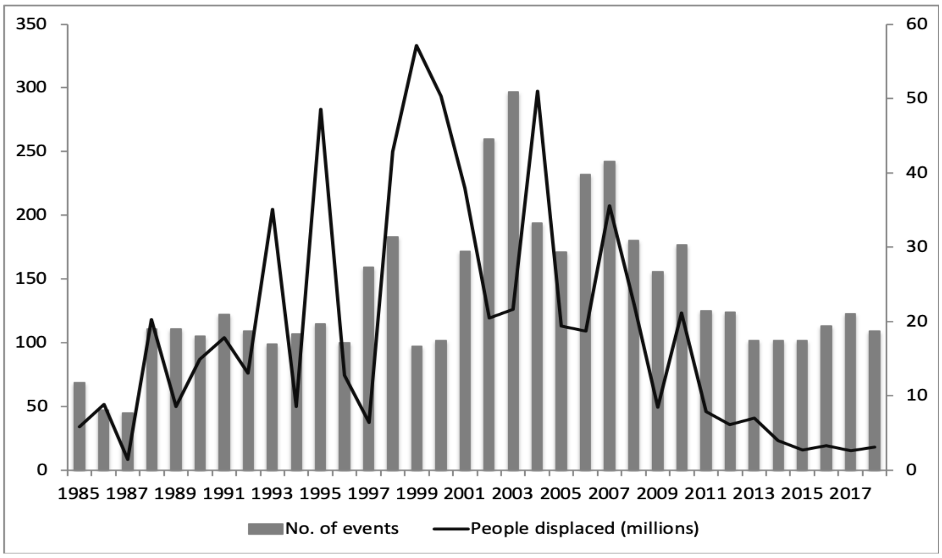
Our data on floods come from the Dartmouth Flood Observatory (DFO) archive (Brakenridge 1985–present). The DFO database includes information by event on the location, timing, duration, damage, and estimates of the number of people killed and displaced, for thousands of flood events worldwide from 1985 to the present, compiled from media estimates and government reports. The version of the archive that we extracted (in August 2018) includes over 4,600 separate flood events over the period 1985-2018. Of these, just over 3,300 occurred in countries for which we have urban disorder data from the USD dataset. Figure 2.A shows the locations of each of these flood events, while Figure 2.B shows the total number of flood events per year, as well as the number of people displaced by these events, over time.

Figure 2.A. Flood events



Note: The map shows the location of each of the flood events in the DFO archive. Dots are proportional to the area affected for each event, with events that occurred in countries in our sample highlighted in black.

Figure 2.B. Flood events and number of people displaced per year (in millions)



Note: The figure shows the number of flood events recorded per year (left hand axis) and the total number of people displaced by those events worldwide (right hand axis, in millions), according to data from the Dartmouth Flood Observatory archive.

Particularly useful for our purposes are a set of shapefiles that define the areas affected by each flood event in the archive. While these shapefiles often cover fairly broad areas (these are not inundation maps), they allow us to do several important things. First, we can distinguish floods that have impacted directly on the cities in our data from those that have affected other areas within the same country.[8] Many flood events impact directly on large cities, displacing people already living in cities. These events would not therefore be expected to increase the population of those cities. By contrast, flood events occurring outside of major cities, and displacing population, may cause (some of) those displaced to move to the city. Using geographic information system software, we overlap the flood shapefiles obtained from DFO, with coordinates of the cities in our data, to distinguish flood events that overlap with the city from those that affect other areas within the same country.[9] Based on this categorization, we construct a measure of floods, which is the sum of the number of people displaced by flood events occurring in country *j* in period *t*, which did not overlap with city *i*. Second, we can use information on the location of each flood to weight our flood variable(s) by the distance to the city, within the same country, where we observe social disorder. Specifically, we take the distance from the centroid of the area affected by each flood event (as defined by the DFO data) to the coordinates for the city provided in the USD data.

Third, and most importantly, we can use the shapefiles for each of the more than 3,300 flood events that occurred in our sample countries, to construct a measure of population exposed (or potentially exposed) to flooding for each event, by overlapping the shapefiles with gridded population data for the affected area. While the natural hazard that leads to flooding (rainfall, storms etc.) may be exogenous with respect to socio-economic outcomes of interest, the number of people actually displaced by a given flood event is likely to depend on a range of socio-economic factors, including income, infrastructure and the efficiency of emergency response planning (which in turn might be related to the quality of local governance), which may also play a role in determining urbanisation and social disorder outcomes, raising endogeneity concerns. Our measure of population exposure to flooding, by contrast, is plausibly exogenous with respect to the

[8] As per the DFO website, Archive Notes: "Polygons representing the areas affected by flooding are drawn in a geographic information system program based upon information acquired from news sources. Note: These are not actual flooded areas but rather the extent of geographic regions affected by flooding." (accessed November 2018).
[9] Population movement inside a country is much more likely (and easier) than across a border. For that reason, and for simplicity of the analysis, we do not consider the possibility of cross-border movements of population.

outcomes we care about, since it is defined simply by the intersection of the area affected by flooding (broadly defined) and the population of affected areas.[10] Thus, in our main analysis, we measure *Floods* as the sum of population exposed in each affected gridcell in country j, during period t, weighted by the distance of each gridcell to the coordinates for city i (excluding gridcells within a 50km radius of the city centroid).[11]

Urban Population and other data:

For urban population, we use data from the United Nations' World Urbanization Prospects, which includes observations of city population every five years from 1950–2015. In line with the urban economics literature, cities are considered not as administrative units but as functional urban areas. This means that we consider population in the whole urban agglomeration. Considering population in the whole urban agglomeration is not only more appropriate to capture the reality of urban residents, but also makes the comparability across cities in different countries easier.

Additional data, used mainly as part of our robustness checks, include information on: GDP per capita, economic growth and total population (from the Penn World Table), as well as measures of urban-level sanitation (from World Bank-World Development Indicators), and national level armed conflict, based on the UCDP/PRIO Armed Conflict Data Set (Uppsala Conflict Data Program and Peace Research Institute Oslo, 1946–2008), and democracy, based on the Polity IV data (Marshall and Gurr, 1800–2013).

[10] Population grids are obtained from GRUMPv1 (CIESIN 2011) and observed at a fixed point in time 1990, such that for most of the flood events in our data, the population data we use cannot have been affected by those (subsequent) flood events.

[11] The 50km threshold is based on the land area of the biggest cities in the world (from http://www.citymayors.com/statistics/largest-cities-area-125.html , accessed in November 2020). According to these data, the biggest city in the world by land area is New York City, at almost 9,000 square km. If this area were a perfect circle the radius would be 50km. The rationale for excluding these gridcells from the measure is that we focus on displacement to cities due to flooding elsewhere in the same country. In this case, we keep information on all flood events, and just exclude from our measure the exposed population already living within (or very close to) affected cities.

3.2. Descriptive analysis and stylized facts

We have 103 cities in 89 countries in our global sample, for the period 1985-2015, such that the maximum number of observations is 618.[12] Table 1 presents summary statistics for our main variables, aggregated to 5-year periods, while Table A.2 in Appendix A shows summary statistics for the numbers displaced by flooding (according to DFO estimates) as well as our measure of population exposed.

Table 1. Summary statistics for main variables, city-5-year aggregation

Variable	Obs	Mean	Std. Dev.	Min	Max
Social disorder					
N_ Events	618	9.39	15.28	0	208
Pr(Events)	618	0.86	0.35	0	1
N. Events (per million)	606	5.01	8.72	0	70.03
City_Pop (millions)	606	3.88	5.18	0.06	36.90
Population displaced by floods (in millions)	618	2.45	15.02	0	222.22
Floods (exposure)	618	8.30	5.06	0	15.90

Notes: N_Events is a count of the number of disorder events per 5-year period observed in a given city. *Pr(Events)* is a binary indicator for whether or not a city experienced any disorder events in a given 5-year period. Population displaced by floods aggregates estimates of people displaced by all flood events that occurred in country *j* in period *t*, which did not overlap with city *i*. Finally, *Floods* (exposure) is our measure of population in affected gridcells for all flood events in country *j* in period *t* (in logs), weighted by distance from each gridcell to city coordinates (excluding gridcells within 50km of the city centroid).

Descriptively exploring our dataset, we can highlight some relevant stylized facts. First, we see that, on average, each city in our dataset experienced 9.4 urban disorder events per 5-year period.[13] Second, in terms of city population, the average city in our sample has 3.9 million inhabitants. There is also a clear upward trend in city populations for almost all counties; if we compare 1985 with 2010, the average goes from 2.8 to 5.1 million. Third, when looking at floods, the average population displaced by flooding per country in our sample over 5 years is 2.45 million. By country-period, we see some very large numbers, both in terms of events and people displaced. In China, in the 1990-1994 period there were 49 separate flood events, which displaced a combined

[12] Two cities in our sample, Taipei and Lhasa, are missing from the UN WUP data on city population.
[13] The max values of 208 events refers to Bagdad in the 2005-2009 period.

total of 41 million people. To provide context, the average number of people displaced by flooding per year across our sample is equivalent to 8.8% of the total population in the cities that we study. As an example, the number of people displaced by flooding in Bangladesh per year regularly exceeds the equivalent of 50% of the population of Dhaka.

Finally, Figures 3.A and 3.B show the association between our main variables. We use *binscatters* and control for time-invariant city-specific characteristic (i.e., city fixed effects) as well as period fixed effects. In this way, Figures 3.A and 3.B only consider the within-city evolution over time (what we are after). As shown, an increase in people displaced by floods shows a positive association with city growth (Figure 3.A), and city growth shows a positive association with the evolution in the number of urban disorder events (Figure 3.B).

Figures 3.A and 3.B. Association Between Main Variables

Fig. 3.A: Floods and City Population

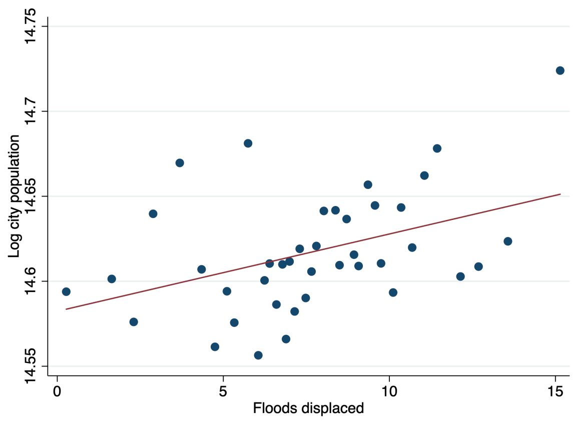
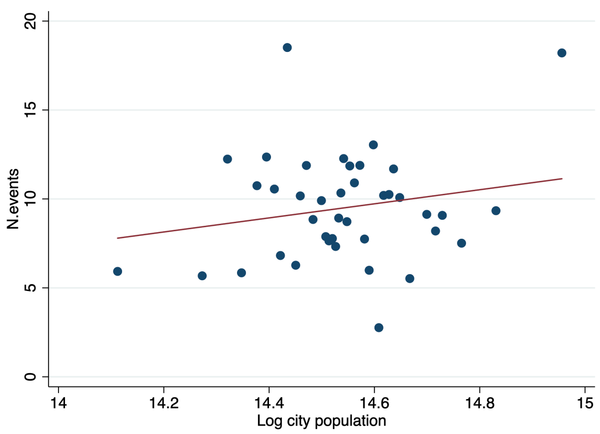


Fig. 3.B: City Population and Urban Disorder Events



Note: Figures show *binscatters* using all available observations for each pair of variables, based on our 5-year city panel used in our empirical analysis. Each dot is a "bin" representing 15 observations in our dataset. Panel A shows the association between people displaced by flood events that occurred elsewhere in the country (in logs) and city population (in logs). Panel B shows the association between city population (in logs) and the number of disorder events in the city. Both *binscatters* control for time-invariant city-specific characteristic (i.e., city fixed effects) as well as period fixed effects.

4. Empirical Analysis

Our empirical analysis relies on a panel of 103 cities observed across the period 1985-2015. At the city level, we observe population and urban disorder events, and as described in the previous section, we have constructed novel city-specific measures of exposure to floods.

4.1. Displacement and urban social disorder:

Our aim is to test whether (and how) displacement of population into cities can drive urban social disorder. Consequently, we begin by estimating a "reduced-form" of our main hypothesis: that floods occurring elsewhere in a country, by displacing population into cities, are associated with urban disorder in those cities. For this, we estimate regressions of the following form:

$$Disorder_{ijt} = \alpha_1 + \beta_1 Floods_{ijt-1} + \gamma_t + \theta_i + \epsilon_{ijt} \qquad (1)$$

where $Disorder_{ijt}$ represents alternatively a count of the number of disorder events, or a binary indicator of whether or not any disorder event has occurred, in city *i* in country *j* in period *t*, where *t* aggregates across five-year periods from 1985-2015.[14] For $Floods_{ijt-1}$, we consider three alternative measures (as explained in Section 3.1). First, the total number of people displaced by floods that impacted elsewhere in the country. Second, weighting by distance to the city *i*.[15] Finally, our preferred measure of distance-weighted population exposed. This novel measure of exogenous variation in exposure to flooding allows us to identify a causal effect of displacement due to flooding on urban social disorder.

Equation (1) is estimated using a Negative Binomial model when $Disorder_{ijt}$ is measured as a count of disorder events for a given city-period observation. This approach tests the *intensive* margin

[14] In our main specifications, we aggregate the data to 5-year periods to facilitate inclusion of city population, which is only observed every 5 years and which is essential to testing the main mechanism that we propose linking floods to urban disorder. However, we also checked our reduced form relationship between floods and disorder using an annual panel (results available upon request).

of the effect of floods (and city population) on the frequency of disorder events. These specifications include city fixed effects, θ_i, to control for time-invariant characteristics of cities. Alternatively, Equation (1) can be estimated using a probability (*xtprobit*) model when $Disorder_{ijt}$ is measured as a binary indicator for city-period observations with zero or nonzero counts of disorder events.[16] In this case, Equation (1) tests the *extensive* margin of the effect of floods (and city population) on the likelihood of urban disorder. In all specifications we include period fixed effects, γ_t , to control for global yearly shocks, and bootstrap the standard errors, ε_{it}, by the Jackknife method.

Table 2 present our results for estimates of Equation (1), for our different ways of measuring *Floods*. Columns 1 to 3 consider the extensive margin (i.e., the probability of disorders) while columns 4 to 6 consider the intensive margin (i.e., the count of disorders). In Columns 1 and 4, *Floods* is measured by the log of population displaced. Columns 2 and 5 use our distance-weighted version of the number displaced, while Columns 3 and 6 use our preferred measure of distance-weighted population exposed.

In all columns, we find a positive and highly significant coefficient on *Floods*. These results suggest that the numbers displaced by floods occurring outside major cities are strongly associated with both the number of disorder events occurring in those cities and with the probability of observing disorder events in a given city. Moreover, the increased magnitude of the estimated effect when weighting by distance (comparing Columns 1 and 2, and also comparing Columns 4 and 5), is significant. It suggests that the proximity of flooding to the city plays a role in the magnitude of the observed effects, or in other words, whatever mechanism is causing the observed relationship between flooding and disorder appears to be operating across space.

[16] Where we estimate Equation (1) using a probit model, the specification includes random effects, as opposed to fixed effects. If we include city fixed effects (or dummies), the relative lack of variation in the binary outcome results in a number of cities being dropped (due to collinearity) with a substantial decrease in observations and precision of the findings.

Table 2. Effect of floods on urban social disorder, extensive and intensive margins

	(1) Pr(event)	(2) Pr(event)	(3) Pr(event)	(4) No. of events	(5) No. of events	(6) No. of events
Floods	0.056*** (0.020)	0.090** (0.040)	0.092*** (0.025)	0.029** (0.012)	0.050** (0.021)	0.045*** (0.016)
City effects	RE	RE	RE	FE	FE	FE
Observations	515	515	515	505	505	505
No. of cities	103	103	103	101	101	101

Notes: Columns 1-3 estimated by Probit model with random effects. Columns 4-6 estimated by Negative Binomial model with city fixed effects. All regressions include time-period fixed effects. Columns 1 and 4 use the numbers displaced by floods (in logs). Columns 2 and 5 use a distance weighted version of this. Columns 3 and 6 use population exposed (weighted by distance, and in logs). The floods variable is lagged in each case, so that floods in 1985-1989 predict disorder in 1990-1994 etc. Robust standard errors (in parenthesis) are bootstrapped by the Jackknife method. *** p<0.01, ** p<0.05, * p<0.1.

Our results in column 3 in Table 2 suggest that for one standard-deviation increase in our exposure to floods variable we see a 7 percentage points increase in the probability of a city having a disorder event in a 5-year period. In terms of frequency (i.e., intensive margin), using results in column 6, a one-standard deviation increase in our exposure to floods variable results in a 23% increase in the incidence of social disorder events.[17]

In Appendix B, we provide several robustness checks to our results in Table 2. First, in Table B.1, we show that our results hold for different ways of measuring the intensive margin of social disorder, including measuring the number of events relative to city population. Second, in Table B.2, we control for several time-varying characteristics of countries, including the log of GDP per capita, as well as additional control variables that may be relevant to social disorder in urban areas, such as an indicator for country-periods with ongoing armed conflict, and an indicator of democracy.[18] Finally, in Figures B.1 (for the extensive margin) and B.2 (for the intensive), we consider dynamics and perform a simple placebo test. In both cases, the estimates are positive and significant for the first lag (as in our main results), and decreasing gradually in magnitude thereafter.

[17] For the extensive margin, the marginal effect at the mean is 0.014. Using a one-standard deviation of 5.055, this translates into a 7-percentage point increase. For the intensive margin, the incidence rate ratio is 1.0458. Taking one-standard deviation of 5.055, this translates into a 23% increase.

[18] Where these controls are included alongside $Floods_{it}$, the controls are lagged in order to avoid floods having a contemporaneous effect on these controls.

However, for floods that have not yet occurred (our placebo) we find no significant coefficients, as expected.[19]

4.2. Displacement, city growth and social disorders in urban areas:

According to our results so far, population displacement due to floods (or exposure to floods) is significantly associated with both the probability and the intensity of social disorders in cities. According to insights from the existing literature discussed in Section 2, the positive association between people displaced by floods and urban social disorders is likely to be driven by unplanned city population growth. As shown by Acemoglu et al. (2020) population pressure can lead to conflict. In this sub-section, we test this explicitly by introducing city population in our model for urban disorders, as follows:

$$Disorder_{ijt} = \alpha_1 + \beta_1 Floods_{ijt-1} + \beta_2 CitySize_{ijt} + \gamma_t + \theta_i + \epsilon_{ijt} \quad (2)$$

where $CitySize_{ijt}$ is the population of city *i* (in logs) in country *j* in period *t*.[20] The remaining variables on the right-hand side of Equation (2) are defined as in Equation (1). The idea here is that if the effect of floods on urban disorder operates mainly through the displacement of people into cities, then this effect should be absorbed by the inclusion of the city population variable, and we should see a reduction in the magnitude (and significance) of the effect of floods on disorder when we also control for city population. Table 3 presents results of estimates of Equation 2. As before, in columns 1 and 2 we consider the extensive margin (i.e., the probability of disorders), while in columns 3 and 4 we consider the intensive margin (i.e., the count of disorders).

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[19] Our results are also robust to including country fixed-effects (rather that city-fixed effects), or aggregating the data at the country level. Our results are also robust to excluding outliers.

[20] City population is measured at the beginning of the 5-year period, such that in estimating equation (2), floods in 1985-89 (for example) are associated with CitySize in 1990, which in turn is associated with disorder events over the subsequent 5-year period (1990-94).

Table 3. The role of city population

	(1) Pr(event)	(2) Pr(event)	(3) N_events	(4) N_events
Floods	0.092***	0.073***	0.045***	0.036**
	(0.025)	(0.026)	(0.016)	(0.016)
City population		0.403**		0.249**
		(0.183)		(0.115)
City Effects	RE	RE	FE	FE
Observations	515	505	505	495
No. of cities	103	101	101	99

Note: Floods is measured using the log of population exposed (weighted by distance) and lagged (so, for instance, floods in 1985-1989 predict disorder in 1990-1994). Columns 1 & 2 are estimated by Probit model with random effects. Columns 3 & 4 are estimated by Negative Binomial model with city FE. All regressions include time-period fixed effects. Robust standard errors (in parenthesis) are bootstrapped by the Jackknife method. *** p<0.01, ** p<0.05, * p<0.1.

Results reported in Table 3 show that the magnitude of the coefficient on floods declines when we add city population; the estimated effect of floods on disorder is reduced by about a fifth for both intensive and extensive margins. By contrast, the coefficient on city population is always positive and significant. These findings strongly suggest that (part of) the effect of floods on the probability and intensity of urban disorder is indeed operating via the effects of flooding on city population.[21]

In Appendix Table C.1, we show results similar to those reported in Table 3 but splitting the data according to the classification of disorder events in the USD data; "demonstrations", "riots" and "armed conflict". In line with expectations based on our discussion in Section 2, the role of city population seems strongest when focusing specifically on demonstrations, with the effect of flooding on the intensive margin becoming insignificant when city population is also included (see column 2, panel B of Table C.1).[22] The results also show that, aside from demonstrations, floods also lead to more armed conflict in cities. The inclusion of city population in the regressions again reduces the magnitude of the estimated relationship between floods and

[21] Floods are indeed found to be strongly associated with (increases in) the population in cities in our sample (see for instance column 1 of Table 4), indicating the link between people displaced by floods and the "push" to urban areas.
[22] In regressions reported in Table C.1, where we use subsets of the data, there is less variation in the outcome variable, with some cities experiencing no events of a particular type, and thus are dropped from the sample when including city fixed effects. For this reason, our regressions in Table C.1 use random effects in all specifications.

armed conflict. However, in this case, the effect appears to be less pronounced, indicating that the effect of floods on armed conflict in cities may operate partly through the effects of floods on urban populations, and partly through some other (unidentified) mechanism – likely related to a more general relationship between extreme weather events and conflict, as has been identified in the literature on climate and conflict previously (see for instance Hsiang et al. 2011; Mach et al. 2019).[23]

Push and pull factors, city growth and social disorders in urban areas:

Our results so far suggest that an increase in exposure to flooding is associated with an increase the probability and count of social disorder in cities. And this seems to happen due an increase in the population of the city. However, in developing countries, cities grow due to various reasons. According to the literature, and as discussed in Section 2, when analysing the growth of cities, we can distinguish between "pull" and "push" factors. Pull factors are associated with good city performance, attracting people to the city. By contrast, push factors are associated with deteriorating conditions elsewhere (mainly rural areas) that displace people towards the city, without individuals being particularly attracted by what happens in the city. Floods are precisely a clear push factor; people are forced to move, and the city is a default option. This represents a source of "unplanned" city growth, and it is this unplanned city growth that we argue is associated with social disorder in urban areas.

To test this idea explicitly we implement two related approaches: First, we predict city growth using "push" factors and, separately, "pull" factors, and test the effects of push and pull-driven city growth on disorders. Secondly, we rely on the so-called Control Function Approach

[23] Using our data, in results not reported, we find that floods appear to be related to more intensive national level conflict, but only marginally (if at all) to the probability of national level conflict.

(CFA) implemented by means of a Two-Stage Residual Inclusion (2SRI).[24] In the first step, we predict the evolution of city size on two clear push factors, floods and (national) population growth. In a second step, we run our Equation 1 for disorders in urban areas, including city size but also residuals from the first stage as explanatory variables. The inclusion of the first-stage residuals controls for unexplained city growth, so that our coefficient for city size captures the effect of (changes in) city size explained by our push factors (i.e., floods and population growth).[25]

Results are presented in Table 4. Column 1 presents the result of the first stage, showing that our "push" factors, namely exposure to floods and (national) population growth, are both strong predictors of city size. In Column 2, we predict city population using two "pull" factors; economic growth, which is associated with more employment opportunities and higher wages, and access to sanitation facilities as a proxy for public service provision.[26] In Columns 3-5, we show the effect of these different types of city growth on the count of disorder events.[27] The results show a stark contrast in effects, depending on which prediction of city size we use: *Push-driven city growth* is associated with a higher frequency of disorder events (Column 3 and 5), whereas for *pull-driven city growth* the effect on disorders is negative but not significant (Column 4 and 5). Finally, in Column 6 of Table 4, we show results from our 2SRI estimations based on the CFA described above. Results yield a highly positive and significant coefficient for city size, while a negative and significant coefficient for the residuals of the first stage. This reinforces our idea that it is the increase in city population explained by our push factors (floods and national population) that is

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[24] Like instrumental variables (2SLS), the CFA procedure uses instruments to break the correlation between endogenous explanatory variables and unobservable variables affecting the response. In linear models with one endogenous regressor, CFA (implemented by means of 2SRI) yields identical results to those obtained with 2SLS. 2SRI yields consistent parameter estimates if instruments are valid (see Imbens and Wooldridge 2009 and Wooldridge 2010). See Terza et al. (2008) for a good explanation of 2SRI. For recent papers relying on 2SRI see for instance Castells-Quintana and Royuela 2017.

[25] We consider floods and population growth to have at least two push factors, as is desirable in two-stage estimations. Population growth has been shown as a key push factor explaining fast city growth in developing countries (Castells-Quintana and Wenban-Smith 2020). However, our results hold if we only use floods. Also note that we bootstrap our standard errors (using the Jackknife method) as commonly done when including generated regressors (Wooldridge 2010).

[26] Basic service provision has been shown to be fundamental for the benefits of agglomeration economies that take place in urban areas, and in developing countries access to sanitation facilities is a good proxy for service provision (see Castells-Quintana 2017).

[27] Table 4 presents results of this analysis for the intensive margin of disorder events. An equivalent table showing results for the extensive margin is included in Table C.2 in Appendix C.

associated with more urban disorders, and not the unexplained part of city growth (which would capture pull-driven city growth and is actually associated with *less* urban disorder).[28]

Table 4. Push vs Pull City Growth and Control Function Approach

	(1) City Pop	(2) City Pop	(3) N_events	(4) N_events	(5) N_events	(6) N_events
Floods	0.006**					
	(0.002)					
Total Population	0.855***					
	(0.147)					
Economic Growth		0.005**				
		(0.002)				
Sanitation		0.006**				
		(0.003)				
Push-driven city growth			0.389***		0.458***	
			(0.114)		(0.136)	
Pull-driven city growth				-1.284	-1.396	
				(0.938)	(0.902)	
City population						0.436***
						(0.131)
Residuals from Column 1						-0.336**
						-0.136
City Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	505	376	500	380	373	495
No. of cities	101	98	100	99	97	99

Notes: The outcome in columns 1 and 2 is City Population, in logs. The outcome in columns 3 to 6 is the number of disorder events. Floods is measured using the log of population exposed (weighted by distance). The explanatory variables in columns 1 and 2 are lagged in each case, so that for example floods in 1985-1989 predicts city population in 1990 etc. All regressions include city fixed effects and time-period fixed effects. In columns 1 and 2 standard errors (in parenthesis) are clustered by city, while in columns 3 to 6 they are bootstrapped by the Jackknife method. *** p<0.01, ** p<0.05, * p<0.1.

4.3. Results by motive of disorder

We now review information on each of the 4,200+ events classified as either riots or demonstrations in the Urban Social Disorder dataset (excluding those classified in the USD data as armed conflict[29]) and classify each event into broad categories reflecting the motive of the tensions leading to disorder. First, we divide all the events in eight categories: public good provision (PGP), prices (PRI), sanctions (SAN), ethnicity/race (ETH), religion (REL), unions (UNN),

[28] Identification of our 2SRI estimates rely on the relevance of our instrument, which is shown in columns 1 and 2 (our first stage) of Table 4. Identification also relies on the exogeneity of our *Floods* measure. As explained in the data section, our exposure to floods measure is by construction exogenous to socio-economic outcomes.

[29] This choice reflects our belief that the mechanism(s) we have in mind are less likely to be relevant in explaining armed conflict events, and also the fact that the relationship between population displacement and armed conflict appears to be mediated at least partly via national level conflict, as shown in the previous section.

international migration (MIG) and corruption (COR). We then aggregated these broad categories into three groups. Group 1 includes events related to public good provision (or the lack thereof), prices and wages (i.e., PGP, PRI, UNN). Group 2 includes events related to sources defined by ethnicity, race, religion or geographic origin (ETH, MIG, REL). Group 3 includes events related to political tensions such as corruption, political motives or international sanctions (COR, SAN). Appendix D gives more information on the methodology implemented for the classification, definitions of each group, as well as some examples of disorders in each group.

Following our empirical methodology, described previously, we test how these three categories of events respond to population displacement resulting from flooding and try to disentangle the effects depending on the source of the riot or protest. We expect that the effect of population displacement may manifest primarily on disorders classified as Group 1 (PGP, PRI, UNN). First, the displacement of population into cities leads to an increase in the demand for public good provision, including basic services such as sanitation, access to water and electricity, housing, transportation, police protection and roads. Second, displacement of population from rural to urban areas also increases the demand for food in the cities, leading to a potential increase in food prices. Third, flooding-driven inflow of people increases the supply of labour in urban areas, especially low skilled, leading to more intense competition over jobs and potentially driving wages down.

To get an insight into the urban disorders classified as Group 1, we look at two examples in our sample. The first takes place in February 2007 in Rangoon, Myanmar, where it was reported that the police arrested some protesters following a public demonstration. The protesters were voicing concerns over practical issues, such as commodity prices, health care, education and the unreliability of power supplies. Similarly, in June 2008 in Dhaka, Bangladesh, newspapers reported that in the central town of Savar, garment workers had held strikes to protest rising food prices, low wages and poor conditions, all following a food crisis.

In Table 5, we present results for Equations 1 and 2, but now separating disorders according to the source of the protest, following our categorization. Panel A presents the extensive margin (i.e the probability of disorders) and Panel B the intensive margin (i.e the count of disorders in each category). Columns 1 and 2 use as dependent variable the protests included in Group 1 (PGP, PRI, UNN), columns 3 and 4 use Group 2 (ETH, MIG, REL) and columns 5 and 6 use Group 3 (COR, SAN). In columns 1, 3 and 5, we only look at flooding, while in columns 2, 4, and 6 we control for city population. As expected, we find a positive and significant coefficient for *Floods* in column 1, both in Panel A and B. These results suggest that people exposure to flooding occurring elsewhere in the country is strongly associated with both the frequency and the probability of observing disorder events related to public good provision, wages and/or food prices in urban areas. This is not the case for protests or riots related to "intra-group" tensions (Group 2) or political motives (Group 3). When we control for city population, the estimated effect of floods on Group 1 loses significance, while the coefficient on city population is positive and significant. As in our main results, this finding suggests that the effect on urban disorders of rural-urban displacement due to flooding in rural areas happens mainly through a city size effect. And this happens especially for urban disorders associated with protests related to public good provision, prices and wages.

Table 5. Results by motive of disorder

Panel A: Extensive Margin	(1)	(2)	(3)	(4)	(5)	(6)
	Pr(Group1)	Pr(Group1)	Pr(Group2)	Pr(Group 2)	Pr(Group 3)	Pr(Group 3)
Floods	0.040**	0.027	0.043	0.009	0.025	0.007
	(0.018)	(0.020)	(0.028)	(0.029)	(0.019)	(0.020)
City Population		0.220**		0.466***		0.236***
		(0.101)		(0.162)		(0.090)
Observations	515	505	515	505	515	505
No. of cities	103	101	103	101	103	101

Panel B: Intensive Margin	(1)	(2)	(3)	(4)	(5)	(6)
	N(Group1)	N(Group1)	N(Group2)	N(Group 2)	N(Group 3)	N(Group 3)
Floods	0.043**	0.028	0.052	0.012	0.027	0.004
	(0.019)	(0.022)	(0.050)	(0.045)	(0.028)	(0.028)
City Population		0.236**		0.547**		0.303**
		(0.114)		(0.235)		(0.134)
Observations	515	505	515	505	515	505
No. of cities	103	101	103	101	103	101

Notes: Group 1: PGP/PRI/UNN, Group 2: ETH/MIG/REL, Group 3: COR/SAN. *Floods* is measured using the log of population exposed (weighted by distance), and lagged one period. The specifications in panel A are estimated using a Probit model with random effects. The specifications in Panel B are estimated by NegBinomial model with random effects. All regressions include time-period fixed effects. Bootstrap standard errors (by Jacknife method) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5. Conclusions

In this paper, we study the effect of displacement of population into cities on conflict in urban areas. In particular, we test the effect of people displaced by floods that occurred elsewhere in the same country on urban social disorder, for a panel of large cities in developing countries. To estimate the causal effect of population displacement on urban social disorder, we exploit exogenous variation in the timing and location of population exposure to flooding.

While the existing literature suggests a potential connection between climate, population displacement into cities and conflict in urban areas, we test this connection explicitly in a global panel of cities. Specifically, we find that exposure to flooding elsewhere in the country leads to increased risk and intensity of urban social disorders in large cities. Furthermore, our evidence suggests that the effect of floods on urban disorder happens mainly through the displacement of population, and the "push" of people into cities. By disentangling push vs pull-driven city growth, our findings also help to reconcile previously ambiguous results on the relationship between city population and urban social disorder. We show dramatically contrasting results of these two different types of city growth, with push-driven city growth significantly increasing the probability and count of urban disorders. Finally, by reviewing descriptive information on each of the events included in the Urban Social Disorder dataset, we also find evidence that the effect of city growth on urban conflict is mainly associated with protests and riots related to public service provision, wages and food prices, in line with our hypothesis.

Our findings have important policy implications. As conflict is becoming more urban, our findings highlight the challenges of managing population pressure at the city level. Climatic factors have become an increasing source of unplanned city growth. These include flooding, which already displaces tens of millions of people from their homes each year, with these effects strongly concentrated in developing countries. As climate change worsens, flood risk will increase in many locations around the world, potentially leading to further large-scale displacement of population. These trends, combined with continued population growth and rapid urbanisation in developing countries will create growing pressures on social and economic infrastructure in cities. Finally, the displacement of population into cities can affect labour markets, food prices and public services demands (housing, sanitation, transportation, etc). Governments need to implement programs that respond to the challenges that the arrival of new population brings.

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Online Appendices for:

Population displacement and urban conflict: Global evidence from more than 3300 flood events

By David Castells-Quintana, Maria del Pilar Lopez-Uribe and Thomas K.J. McDermott

Appendix A: Additional information related to Section 3 (Data)

Table A.1: Main variables' definition and sources

Variable name	Definition	Source and time span
Disorder variables:		
Events	All Social Disorder Events (which we measure either as probability or count, as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Participants	Number of participants, excluding missing values (as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Participants_m	Number of participants, filling missing values with median (as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Demonstrations	Demonstrations as defined in the USD data (which we measure either as probability or count, as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Riots	Riots as defined in the USD data (which we measure either as probability or count, as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Conflict	Conflict as defined in the USD data (which we measure either as probability or count, as explained in main text)	Urban Social Disorder – Prio Database, 1960-2014, 103 cities.
Group 1	The number of protests related to Public Good Provisions (PGP), Prices (PRI) and Unions (UNN)	Constructed by author using Urban Social Disorder – Prio Database, 1960-2014, 103 cities. (see Appendix D)
Group 2	Protests related to Ethnicity/Race (ETH), External Migration (MIG) and Religion (REL)	Constructed by author using Urban Social Disorder – Prio Database, 1960-2014, 103 cities. (see Appendix D)
Group 3	Protests related to Corruption (COR) and Sanctions (SAN)	Constructed by author using Urban Social Disorder – Prio Database, 1960-2014, 103 cities. (see Appendix D)
Floods variables:		
Floods (displaced)	The number of people (in logs) displaced by flood events that occurred in country j in period t , which did not overlap with city i .	Constructed by authors using DFO archive data on flood events, 1985-2015 (see main text).
Floods (displaced, weighted by distance)	The number of people (in logs) displaced by flood events that occurred in country j in period t , which did not overlap with city i , weighted by the distance from each flood event centroid to city i.	Constructed by authors using DFO archive data on flood events, 1985-2015 (see main text).
Floods (exposure)	The number of people (in logs) exposed to flood events in country j in period t , weighted by the distance of each populated gridcell to city i (excluding population within 50km of city i).	Constructed by authors using DFO archive data on flood events, 1985-2015, and GRUMPv1 (see main text).
Other variables:		
City pop	City population, in the whole metropolitan area	United Nations' World Urbanization Prospects
Total pop	Total population of the country	Penn World Table
National conflict	Indicator for if a country was experiencing national level conflict in period t	UCDP/PRIO Armed Conflict Data Set (Uppsala Conflict Data Program and Peace Research Institute Oslo, 1946–2008).

Democracy	Indicator for if a country was defined as a democracy in period *t*	Polity IV data (Marshall and Gurr, 1800–2013).
GDP pc	Gross Domestic Product, per capita (in constant US dollars)	Penn World Table
Economic growth		Penn World Table
Sanitation	Percentage of urban population with access to improved sanitation facilities	World Bank-World Development Indicators

Table A.2 Summary statistics for population exposed and people displaced by individual flood events in our data

Variable	Obs	Mean	Std. Dev.	Min	Max
Pop exposed (millions)	4,663	15.8	43.9	4.68E-05	746
People displaced (millions)	4,663	0.14	1.21	0	40
Ratio displaced/exposed	4,663	0.03	0.35	0	17.16

Notes: Population exposed numbers are quite large, given that these represent the total population living in areas affected by flooding, as defined by the overlapping of DFO shapefiles with population grids. Estimates of people displaced are taken directly from the DFO archives.

Appendix B: Additional results to section 4.1.

Table B.1: Effect of floods on urban disorder, different measures for the intensive margin

	(1) N_events	(2) Participants	(3) Participants_m	(4) N_events p.m	(5) Participants_m p.m
Floods	0.045***	0.037**	0.054***	0.046**	0.056***
	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
Obs.	505	495	505	495	495
No. of cities	101	99	101	99	99

Notes: In column 1, the dependent variable is the number of events. In column 2, *Participants* is a measure of the sum of estimated participants in disorder events for given city-5year observation. In column 3, *Participants_m* fills "unknown" participant numbers with the median for that city. Columns 4 and 5 consider events and participants relative to city population (i.e., per million). *Floods* is the log of population exposed (weighted by distance), and lagged one period. All regressions include city and period fixed effects. Robust standard errors (in parentheses) are bootstrapped by the Jackknife method *** p<0.01, ** p<0.05, * p<0.1.

Table B.2: Effect of floods on urban disorder, adding different time-varying controls

	(1) Pr(event)	(2) N_events	(3) Participants_m	(4) N_events p.m	(5) Participants_m p.m
Floods	0.084***	0.047***	0.058***	0.047***	0.061***
	(0.025)	(0.017)	(0.018)	(0.017)	(0.017)
GDPpc	0.011	0.044	0.080	0.153	0.096
	(0.135)	(0.128)	(0.096)	(0.227)	(0.097)
Armed Conflict	0.407	0.078	0.325*	-0.024	0.313*
	(0.391)	(0.210)	(0.179)	(0.240)	(0.177)
Democracy	-0.024	0.131	0.038	0.062	0.017
	(0.294)	(0.162)	(0.201)	(0.195)	(0.197)
Obs	473	466	466	461	461
No. of cities	99	97	97	96	96

Notes: In column 1, the dependent variable is the probability of event (i.e., extensive margin), while in column 2 is the number of events (i.e., intensive margin). In column 3, *Participants_m* fills "unknown" participant numbers with the median for that city. Columns 4 and 5 consider events and participants relative to city population (i.e., per million). *Floods* is the log of population exposed (weighted by distance) and lagged one period. GDPpc also in logs. All controls are lagged one period. Column 1 is estimated by Probit model with random effects. Columns (2)-(5) estimated by Negative Binomial model with city fixed effects. All regressions include period fixed effects. Robust standard errors (in parentheses) are bootstrapped by the Jackknife method. *** p<0.01, ** p<0.05, * p<0.1.

Figures B.1: Effect of floods on the probability of urban disorder (i.e., extensive margin), different lag structures

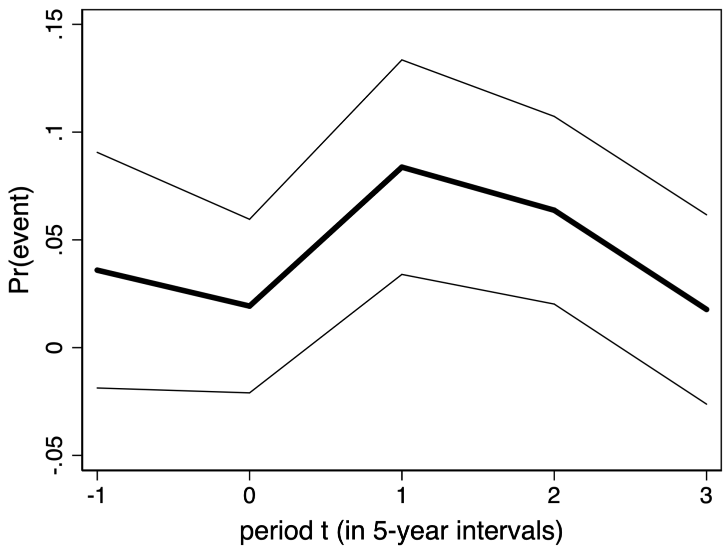
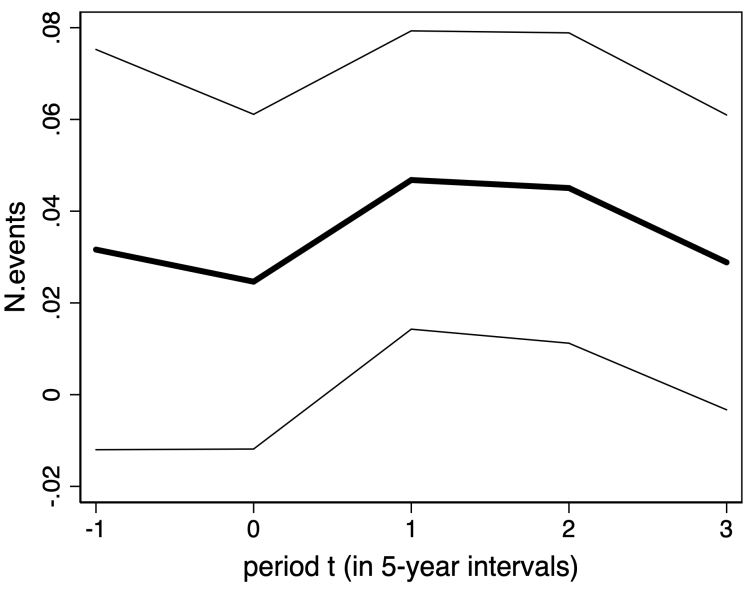


Figure B.2: Effect of floods on the count of urban disorder (i.e., intensive margin), different lag structures



Note: These figures show estimates of regressions based on Equation (1), including one lead and up to three lags. Regressions include time and city fixed (Fig. B2), or random (Fig. B1) effects, and the same set of controls as reported in Table B2 above. As the figures show, there is no effect for disorder events before the floods (at *t-1*), as expected, and the effect of floods on disorder is strongest in the subsequent 5-year period (at *t+1*), declining gradually thereafter.

Appendix C: Additional results to section 4.2.

Table C.1: The role of city population, by event type, extensive and intensive margin

Panel A: Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
	Pr(demos)	Pr(demos)	Pr(riots)	Pr(riots)	Pr(conflict)	Pr(conflict)
Floods	0.081***	0.059***	0.023	0.006	0.053**	0.041*
	(0.022)	(0.022)	(0.019)	(0.021)	(0.021)	(0.023)
City population		0.437***		0.239**		0.224*
		(0.135)		(0.115)		(0.118)
Obs	515	505	515	505	515	505
No. of cities	103	101	103	101	103	101

Panel B: Intensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)
	N_demos	N_demos	N_riots	N_riots	N_conflict	N_conflict
Floods	0.051***	0.028	0.014	-0.004	0.053***	0.040**
	(0.019)	(0.019)	(0.02)	(0.021)	(0.017)	(0.017)
City population		0.329***		0.270**		0.242**
		(0.079)		(0.118)		(0.100)
Obs	515	505	515	505	515	505
No. of cities	103	101	103	101	103	101

Note: Floods is measured using the log of population exposed (weighted by distance) and lagged. Regressions in Panel A are estimated by Probit model. Regressions in Panel B are estimated by NegBinomial model with city. All regressions include city random effects and time-period fixed effects. Robust standard errors (in parenthesis) are bootstrapped by the Jackknife method *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Push and pull city growth, extensive margin

	(1) City Pop	(2) City Pop	(3) Pr(events)	(4) Pr(events)	(5) Pr(events	(6) Pr(events)
Floods	0.006**					
	(0.002)					
Total Population	0.855***					
	(0.147)					
Economic Growth		0.005**				
		(0.002)				
Sanitation		0.006**				
		(0.003)				
Push-driven city growth			0.261*		0.266*	
			(0.15)		(0.144)	
Pull-driven city growth				-0.105	0.136	
				(0.897)	(0.794)	
City population						0.556***
						(0.21)
Residuals from Column 1						-0.032
						(0.199)
Obs.	505	376	510	380	380	505
No of cities	101	98	102	99	99	101

Note: The outcome in Columns 1 and 2 is City Population (in logs). The outcome in Columns 3 to 6 is the probability of event. Floods is measured using the log of population exposed (weighted by distance). The explanatory variables in Columns 1 and 2 are lagged in each case, so that for example floods in 1985-1989 predicts city population in 1990 etc. All regressions include time-period fixed effects. Columns 1 and 2 include city level fixed effects with standard errors clustered by city. Columns 3 to 6 are estimated by Probit model with random effects, with robust standard errors bootstrapped by the Jackknife method. *** p<0.01, ** p<0.05, * p<0.1.

Appendix D: Additional information to section 4.3

Below we briefly explain our methodology for the classification of protests into different categories and groups, and provide some examples of specific cases. First, we divided all the events in eight categories: PGP - public good provision, SAN - sanctions, PRI - prices, ETH -ethnicity/race, REL - religion, UNN - unions, MIG - migration, and COR - corruption. The category SAN includes any protest challenging any law or legislation, restrictions on freedom, punishments or penalties imposed by the country's government or an agreement with another country (usually the United States). Any student protest that does not have explicitly educational grounds is considered to be UNN. Any protest whose cause is purely political (for example, protest by one political party against another) or which has no clear cause (only violence) is attributed a 0 in the PGP column plus is not given any ranking. Protests corresponding to civil wars receive the latter treatment as well.

Specific cases

To classify some specific disorders, we follow some basic criteria used throughout the database. Although not all cases were addressed, it is important to mention that, within the database, an additional column was created providing the additional information that was used to make this decision. This information was usually obtained from news sources (such as the New York Times) and the page where it was found is linked within the database.

- Some disorders are classified as labor protests to raise or set a minimum wage. This could happen because migrants increase the supply of work and the low wage.
- In some cases, no information is found for the specific day. To carry out the classification of the protest, information about the month's context was researched and was used as the basis for the classification.
- In some cases, the protests had several reasons. If these reasons fit several classifications, all of them will be noted in the database. If one of the reasons is migration, the protest will also be classified as PGP. Example: *"Deaths of two protestors in violent clashes with the police on June 26 in Avellaneda, a suburb of Buenos Aires."* After searching for new information, the news outlets

suggest that the protests were due to lack of work, food, freedom of political prisoners, among others.

- In some cases, the protests were made due to past violent acts or in honor of a past event. In this case, a 0 is put but not assigned to a category. Example: *"On April 30 youth members of the Public Chamber groupings marched in Baku to mark the anniversary of the shooting at the State Oil Academy in Baku in April 2009".* New information suggests that the demonstration took place after a student opened fire and killed 13 people at his university.
- Protests over food price increases can be caused due to a migration shock. Example: *"Further protests against price rises in essential commodities on Jan. 23 also ended in violence as police fired tear gas at demonstrators attempting to take over the national television centre in."* The information found suggests that prices increased because a migration shock.
- Protest supported by a large part of the workers of a place may indicate a problem of provision of public goods. Example: *"A general strike called by the UST in early September had been supported by 80 percent of workers, the union claimed."* The protest was classified as PGP and UNN.
- When protests took place in the midst of an independence process, it is not classified as a PGP. Neither are protests demanding peace. Human rights protests are classified as PGP based on the context.
- Protests after natural disasters are considered as PGP. Protests over water or electricity are classified as PGP. Example: *"On May 10, an estimated 2,000 people participated in protests in Port-au-Prince (the capital) againsPréval's government **** Several thousand people participated in a protest in Port-au-Prince (the capital) to demand compensation from the UN following the outbreak of a cholera epidemic in October 2010 ... a series of violent protests erupted throughout Haiti, resulting in the death of at least four people, the closure of the international airport in Port-au-Prince (the capital), and attacks against the INITE headquarters."*