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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 3300 flood events worldwide, as an exogenous source of population displacement. We combine this with city level observations of thousands of urban social disorder events over the period 1985–2015. Exposure to floods is found to be associated with higher intensity of urban social disorder. Our evidence suggests that the effects of floods on urban disorder occur in part 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, prices and wages.

1. Introduction

Conflict is widely recognized 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 3300 flood events worldwide from 1985 to 2015, as an exogenous source of population displacement. We combine this with yearly city-level observations of some 5800 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 remain 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

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governments do not respond to the arrival of new population in cities due to displacement, we may expect protests and riots associated with the increased demands on provision of public services and employment opportunities, and pressures on 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 urbanisation 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 3000 flood events worldwide, to generate a time-varying, population and distance weighted measure of flood exposure. Importantly, we take population data from a fixed point in time, such that identification comes only from variation in the timing and location of floods. We use this exogenous variation in flood exposure to disentangle different types of city growth and to estimate the 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 (USD) dataset, and complement this with additional data sources, 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 Akira, 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 an 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.

The remainder of our paper proceeds as follows: In Section 2, we provide a conceptual framework and 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 the reduced form relationship between people displaced by floods and urban disorders, in Section 4.2 studying the role of city growth (and other potential mechanisms), and in Section 4.3 analysing results by type and motive of event. Finally, Section 5 concludes.

2. Climate, displacement, and conflict in urban areas: A conceptual framework

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 weather shocks occur outside urban areas, it is likely that many of the displaced population end up in cities (Barrios et al., 2006). This displacement of population into large cities creates unplanned city growth. In this section, we examine the mechanisms that potentially link floods, population displacement in rural areas and social disorder in cities, drawing on insights from a number of strands of related literature.

2.1. Climate and conflict

Climate change can affect the economic opportunities of different groups within societies, and trigger conflict over natural resources and the distribution of power. In this spirit, a growing literature has studied the relationship between climate and nation-wide conflict, in many cases using climatic variables (mainly changes in rainfall patterns) as a source of exogenous income shocks (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).

In terms of the mechanisms that relate climatic disruptions with conflict, the literature has suggested at least five distinct mechanisms. A first body of literature focuses on access to public goods in rural areas, such as water or scarcity of renewable resources (Kahl 2006; Eriksen and Lind 2009; Hauge and Ellingsen 1998). A second group of authors focus on the effect of droughts and floods on food prices, leading to disputes between rural producers and urban consumers (see for instance Alexandratos 2008). 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 ((Bertinelli and Strobl, 2013); Acevedo, 2014). A fourth mechanism relates to the effects of weather on overall economic growth, with economic discontent leading to public disorder and conflict (i.e., Miguel et al., 2004; Barrios et al., 2010; Jensen and Gleditsch 2009). 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 a scarcity of food supply that increases prices and an excess of demand of public goods, both of which can increase social tensions, and potentially conflict, in cities (Hendrix and Salehyan, 2012; Taraz et al., 2021)). To the best of our knowledge, this connection between population displacement as a result of climate disruptions, and subsequent conflict, has not been explicitly tested in the literature to date.

2.2. Climate, displaced population and unplanned city growth

The literature has already shown how weather shocks can foster unplanned urbanisation and city growth in Sub-Saharan Africa (Barrios et al., 2006; Bruckner, 2012; Henderson et al., 2014, 2017). Cattaneo and Peri (2016) and Castells-Quintana et al. (2021) show that this happens globally, with climate change and natural disasters altering the whole spatial distribution of population and economic activity. However, as noted, the empirical climate-conflict literature 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 as a potential driver of unplanned city growth, and in turn of urban disorder.

2.3. Unplanned city growth and urban social disorder

Unplanned urbanisation, due to displacement, can have important consequences for city dwellers. 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; Tir and Diehl 1998; Gizewski and Homer-Dixon 1995). The displacement of population into cities can also affect labour markets, 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, especially in those cities with high levels of informality (Reuveny 2007). Second, migration into cities can lead to increases in prices. In the case of food, this can be due to a combination of an increase in the demand in cities and a decrease in the supply due to climatic disruptions in rural areas. This was the case of Morocco in 1980 (Swearing, 1992). This effect can occur over a relatively short period of time, worsening living conditions, underlining grievances and potentially driving the rise of urban social disorders. Third, the displacement of population into cities leads to an increase in the demand for basic public services, including housing (Depetris-Chauvin and Santos, 2018) 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 social frictions may arise. It is likely that this effect is observed in the medium to longer-term.

Despite the range of mechanisms that potentially link fast (unplanned) city growth and conflict in urban areas, there is relatively limited literature that has empirically tested the relationship between the two (exceptions include Buhaug and Urdal, 2013; Ostby 2016 and Bhavnani and Lacina 2015). To date, as noted in the introduction, the results from this literature have been mixed. 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 conflict over these scarce resources, especially i) when the increase in population is not accompanied by increases in productivity or physical and human capital investments, and ii) when economies experience negative (economic or environmental) shocks. We follow Acemoglu et al. (2020) by testing the effect of population pressure on conflict, in our case using flooding occurring elsewhere in the same country as an exogenous shock and the 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. The urban social disorder 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. Below we explain our key variables and sources. Table A.1 in Appendix A gives definitions and sources for the main variables considered.

3.1. Data sources and main variables

3.1.1. 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).¹ This dataset contains information on social disorder events occurring in capitals and other major cities of the developing world over the period 1960–2014. Fig. 1 shows the locations of the 103 cities included in the USD data, reflecting the intensity of disorder events by city and showing important variation across regions in developing countries, while Figure A.1 in Appendix A shows the number of disorder events and the estimated total number of participants in these events from the USD data.

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 9000 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).²

We code the information in the dataset and construct measures for the intensity of disorder at the city-year level. Our primary measure is a count of the number of events per million inhabitants for every city-year observation. This approach tests the *intensive* margin of the effect of floods (and city population) on the frequency of disorder events. For robustness, we also estimate effects for alternative outcome variables, including i) the number of participants in each disorder event, ii) a count of fatal events only, and iii) a binary indicator for whether a given city experienced any disorder events in a given period, which captures the *extensive* margin of disorder (i.e., probability of disorders) (See Table B.1 and B.2). We also analyse sub-sets of the USD data that are most likely related to our primary mechanisms of interest – i.e. population displacement to cities. First, we separate out events labelled as demonstrations and riots in the USD data, as distinct from those labelled as 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. Examining each of the incidents in the USD data labelled as either riots or demonstrations one by one, and cross-checking against additional data sources, we classify each event according to the motivation of the disorder and explore heterogeneity in our results by motive of disorder (see Section 4.3).

3.1.2. 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 4600 separate flood events over the period 1985–2018. Of these, over 3300 occurred in countries

¹ Available from <https://www.prio.org/Data/Armed-Conflict/Urban-Social-Disorder/> (accessed November 2018). The USD dataset is chosen to measure outcomes given our focus on social disorder occurring in cities, and the inclusion in this dataset of a range of disorder events including riots, demonstrations and conflict events not involving government or other “organized” forces, that would not show up in other standard conflict databases, such as the UCDP/PRIO Armed Conflict Dataset (see Högbladh, 2021; and Pettersson 2021). The ACLED conflict dataset also covers this broader range of events, but has the drawback that for many regions and countries around the world it is only available since the late 2010s (in many cases only since 2018).

² Of the more than 9000 disorder events recorded in the USD data, some 5800 occurred during our sample period (1985–2014) and are included in our empirical analysis.

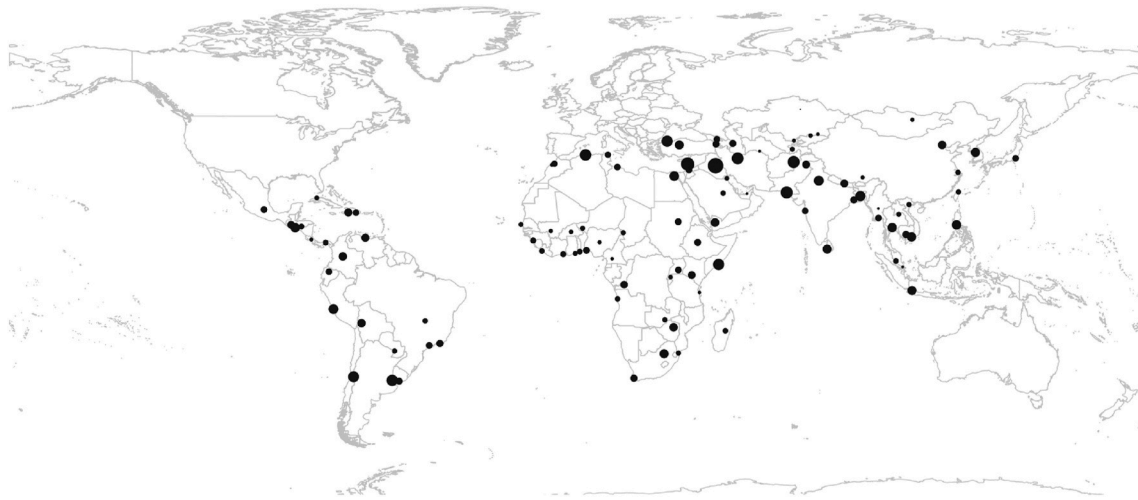


Fig. 1. Urban Social Disorder events. *Note:* Each black dot on the map represents one city included in the USD data. Dots are proportional to the total number of events for that city in the USD data.

for which we have urban disorder data from the USD dataset. Fig. 2 shows the locations of each of these flood events, while Figure A.2. Shows the total number of flood events per year, as well as the number of people displaced by these events.

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 the cities in our data from those that have affected other areas within the same country.³ 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.⁴ 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 weigh 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 3300 flood events that occurred in our sample countries, to construct a measure of the 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 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. 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.⁵ 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 50 km radius of the city centroid).⁶

3.1.3. Urban population and other data

For urban population, we use data from the United Nations' World Urbanisation Prospects (UN-WUP). 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, which is more appropriate to capture the reality of urban residents, and also makes the comparability across cities in different countries easier. UN-WUP provides city population data from 1950 to 2015, but only including observations every five years. In our main analysis, based on an annual panel, we interpolate between observations in UN-WUP population data to fully exploit our urban conflict and floods data (which do have annual variation). As robustness, we replicate our main findings i) using the original UN-WUP city population data for 5-year intervals, by aggregating our urban conflict and floods data, and ii) using annual city-population data for the largest city in each

³ 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).

⁴ 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.

⁵ As a robustness check we replicate our main results restricting the outcome to disorder events that occurred after 1990. Results remain effectively unchanged by this restriction.

⁶ The 50 km 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 9000 square km. If this area were a perfect circle the radius would be 50 km. 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.

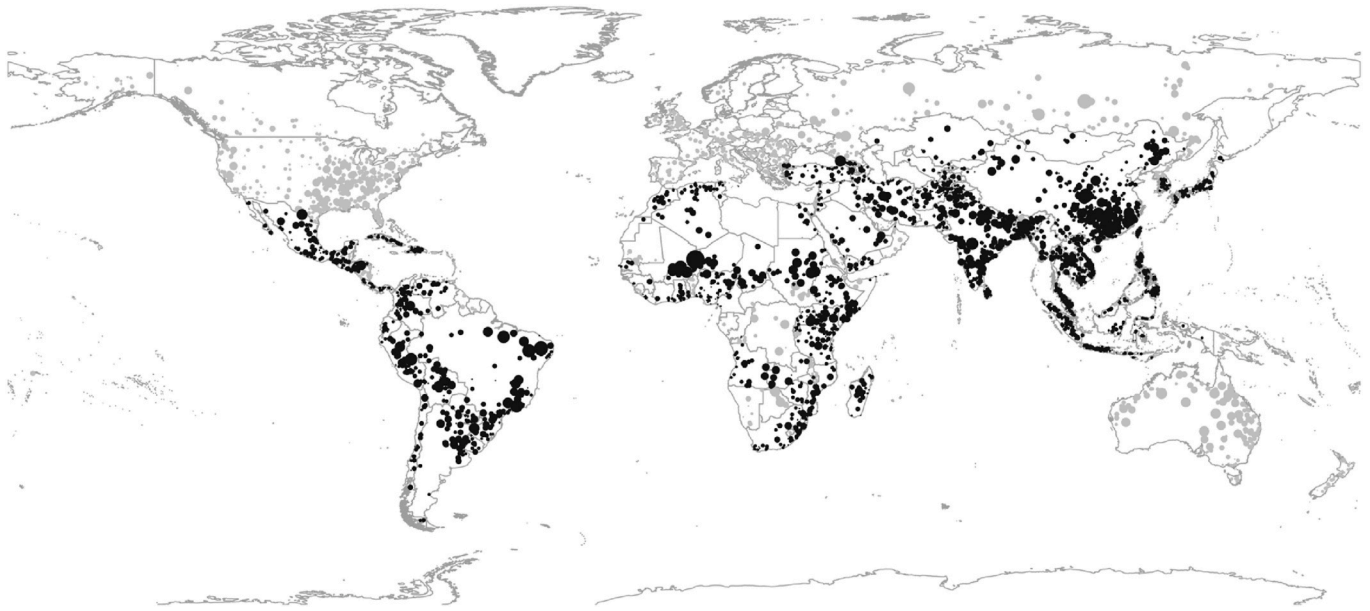


Fig. 2. Flood events. *Note:* The map shows the location of each of the flood events in the DFO archive. Dots are proportional to the area affected for each event, with events that occurred in countries in our sample highlighted in black.

country only, based on urban data obtained from Our World In Data (OWID).⁷

Additional data used in the analysis include information on: GDP per capita and measures of urban-level sanitation (from World Bank-World Development Indicators), economic growth and total population (from the Penn World Table), 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 Robert Gurr, 1800–2013).

3.2. Descriptive analysis and stylized facts

We have 103 cities in 89 countries in our global sample, for the period 1985–2015.⁸ Table 1 presents summary statistics for our main variables for the city-year panel, 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, for individual flood events.

Descriptively exploring our dataset, we can highlight some relevant stylized facts. First, we see that each city in our dataset experienced 1.9 urban disorder events per year, on average over our sample period.⁹ Second, in terms of city population, the average city in our sample has 4 million inhabitants. Third, when looking at floods, the average number of people displaced by flooding in our sample is 490,000 per year.¹⁰ To provide context, the average number of people displaced by flooding per year across our sample is equivalent to 12% of average city population in the cities that we study. As an example, according to these data the number of people displaced by flooding in Bangladesh per year regularly exceeds the equivalent of 50% of the population of Dhaka.

⁷ OWID urban data is based on underlying data from the UN-WUP, UN-Habitat and the World Bank's World Development Indicators; see Ritchie and Roser (2018).

⁸ Two cities in our sample, Taipei and Lhasa, are missing from the UN-WUP data on city population.

⁹ The max value of 83 events recorded in a single year refers to Baghdad in 2005.

¹⁰ This is restricting to floods that occurred in country j in year t where the flood affected areas, according to the Dartmouth Flood Archive data, did not overlap with city i .

Table 1

Summary statistics for main variables, city-year panel.

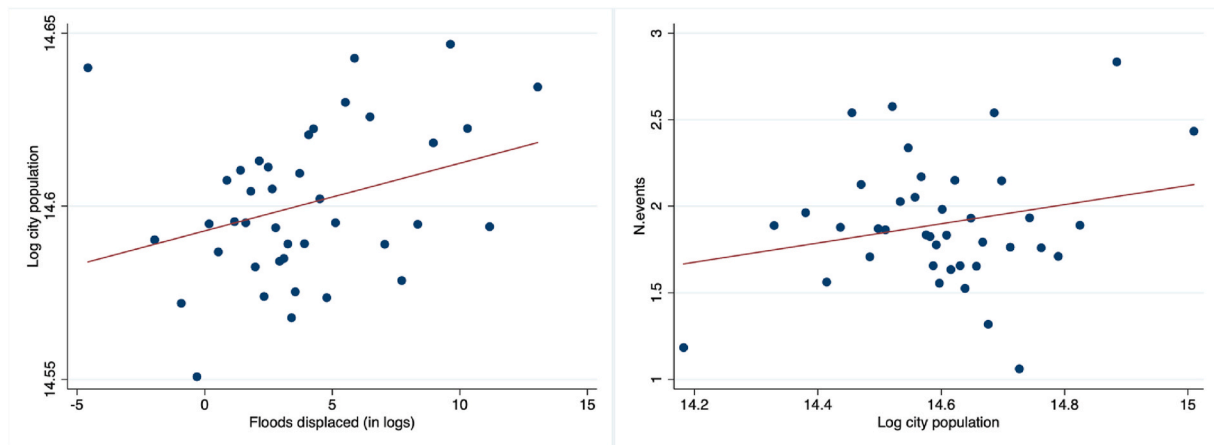
Variable	Obs	Mean	Std. Dev.	Min	Max
Urban Social disorder					
N. Events	3090	1.88	3.88	0	83
N. Events (per million)	3030	0.95	2.12	0	27.13
City Pop (millions)	3030	4.07	5.35	0.06	37.20
Population displaced by floods (in millions)	3090	0.49	5.04	0	160
Floods (exposure, in logs)	3090	4.56	5.18	0	14.92

Notes: N.Events is a count of the number of disorder events per year observed in a given city. N.Events (per million) is the count of disorder events per million inhabitants in the city (based on UNWUP city population data). City population data from UNWUP are unavailable for two cities in the USD data, Taipei and Lhasa. City Pop (millions) is based on UNWUP estimates of population in each city, interpolated to generate an annual series. Population displaced by floods aggregates estimates from the Dartmouth Flood Observatory data of the number of people displaced by all flood events that occurred in country j in year 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 50 km of the city centroid).

Finally, Fig. 3A and 3B shows 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 year fixed effects. In this way, Fig. 3A and 3B 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 (Fig. 3A), and city growth shows a positive association with the number of urban disorder events (Fig. 3B).

3.2.1. Disorder events

Note: Figures show *binscatters* using all available observations for each pair of variables, based on our annual city panel used in our empirical analysis. Each dot is a “bin” representing 75 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



Figs. 3A and 3B. Association between main variables. A: Floods and city population. B: City population and urban disorder events. *Notes:* Figures show *binscatters* using all available observations for each pair of variables, based on our annual city panel used in our empirical analysis. Each dot is a “bin” representing 75 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 annual shocks that are common across all cities (i.e., year fixed effects).

binscatters control for time-invariant city-specific characteristic (i.e., city fixed effects) as well as annual shocks that are common across all cities (i.e., year fixed effects).

4. Empirical analysis

Our empirical analysis relies on a panel of 103 cities observed annually 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. Floods 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 people displaced by floods occurring elsewhere in a country are associated with urban disorder in those cities. For this, we estimate regressions of the following form:

$$Disorder_{ijt} = \alpha_1 + \beta_1 Floods_{ijt} + X_{jt}\delta + \gamma_i + \theta_t + \varepsilon_{ijt} \quad (1)$$

where $Disorder_{ijt}$ is our count of the number of disorder events per million inhabitants in city i in country j in year t , or any of our alternative measures for disorders. For tables in main text, we use annual variation of the data. For robustness in Appendix B, t aggregates across five-year periods from 1985–2015.¹¹ For $Floods_{ijt}$, 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 . Finally, our preferred measure of distance-weighted population exposed. This novel measure of exogenous variation in exposure to flooding allows us to identify the effect of floods on urban social disorder.

Table 2 presents our results for estimates of Equation (1), for our different ways of measuring *Floods*. Columns 1–3 use all cities in our sample, while columns 4–6 use largest city per country only. 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*. Our results suggest that floods occurring outside major cities are strongly associated with the intensity of disorder in those cities. In terms of magnitude, our results suggest that a one-standard deviation increase in exposure to floods results in a 16% short-run increase in the intensity of social disorder events.¹² The increased size of the estimated coefficient when weighting by distance (comparing Columns 1 and 2, and also comparing Columns 4 and 5) is also noteworthy. 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.

Tables in Appendix B show the robustness of our main results. In Table B.1, we show that results hold when we exclude controls and use different samples, for instance restricting the sample to the largest city per country only. In Table B.2, we show robustness to the use of alternative measures for disorders, including i) a binary indicator for whether a given city experienced any disorder events in a given period (i.e., probability of disorders), ii) number of participants in each disorder event, and iii) fatal events only.¹³ In Table B.3 and Figure B.1, we show results aggregating over 5-year intervals. Finally, we consider different lags and perform two placebo tests (see Tables B.4 and B.5): first, a temporal one, considering floods that have yet not occurred, and second, a spatial one, distinguishing between flood events where there is an alternative (non-USD) city nearby vs floods where there is not.¹⁴

Fig. 4 shows the dynamics in the floods-disorders relationship. Estimates are positive and significant for the contemporaneous effect, and again for the third and fourth lags (i.e., a longer-term effect). For floods that have not yet occurred (our placebo) we find no significant coefficients, as expected. In terms of magnitude, we see that over the subsequent 5 years, a one-standard deviation increase in flood exposure at time t , produces up to a 33% increase in the intensity of social

¹¹ The 5-year aggregation is justified on two main reasons. First, so not to rely on interpolations of population data, which is only available every 5 years. Second, to capture the hypothesis that it may take time to translate a flood shock into movement of people to social or economic tensions in urban areas.

¹² Based on the results reported in Column 3, the incidence rate ratio is 1.0305. Taking one-standard deviation in floods exposure of 5.18, this translates into a 16% increase.

¹³ In Table B.2, we also test for different estimation techniques and clustering of errors. For instance, in columns 1–4, we use OLS rather than negative binomial, and cluster errors by city.

¹⁴ As expected, our results are stronger and significant when there is no alternative city to migrate for people displaced by floods.

Table 2

Effect of floods on urban social disorder, intensive margin.

	(1)	(2)	(3)	(4)	(5)	(6)
	No. of events per million	No. of events per million	No. of events per million	No. of events per million	No. of events per million	No. of events per million
Floods	0.022*** (0.006)	0.042*** (0.013)	0.030*** (0.008)	0.017** (0.007)	0.031** (0.013)	0.028*** (0.008)
Controls	YES	YES	YES	YES	YES	YES
City and year effects	YES	YES	YES	YES	YES	YES
Observations	2746	2746	2746	2398	2398	2398
No. of cities	98	98	98	86	86	86

Notes: Columns 1–6 estimated by Negative Binomial model with city and year fixed effects. The dependent variable is in all cases number of disorder events per million inhabitants in the city. In columns 1–3 we use all cities in our sample (using population data from UN-WUP data), while in columns 4–6 we use largest city per country only (using population data from OWID data). 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). Robust standard errors (in parenthesis) are bootstrapped by the Jackknife method. ***p < 0.01, **p < 0.05, *p < 0.1.

disorders (more than twice the estimated contemporaneous effect of a 16% increase in disorder, noted previously). This compounded effect over time is something that we observe in the descriptive information on disorder events. For example, in Morocco in 1980s, protests started in response to population pressure in cities as a consequence of climate shocks during previous years, which lead numerous families to be displaced from rural to urban areas. Similarly, in Nepal and Pakistan, climate shocks forced rural population to migrate to cities, increasing food prices and the demand on public services, in particular electricity and water. Population pressures in urban areas, in this way, were at the root of the protests that started in Katmandu in 1992 and in Karachi in 2001.¹⁵

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) that occurred elsewhere in the same country is significantly associated with the intensity of social disorders in cities. According to insights from the existing literature discussed in Section 2, the connection between displacement and urban conflict can partly be explained by the increased population pressure in cities (as for instance shown by Acemoglu et al., 2020). To investigate the importance of these population-pressure mechanisms linking floods with urban disorder, we present the results of a simple mediation analysis.¹⁶ The general goal of mediation analysis is to disentangle average treatment effects operating through two distinct channels: (i) *indirect effects* arising from the effect of treatment on measured mediators, and (ii) *direct effects* that operate through other channels, including via changes in mediators that are not observed and via changes in the mapping between mediators and outcomes (Fagereng et al., 2021).

The main estimating equation for the mediation model can be written as follows.¹⁷ For simplicity here we suppress the time and location indices:

$$Disorder_f = \alpha_1 + \beta_1 Floods + \sum_{m \in \mathcal{M}_f} \beta_m^m \pi_f^m + X\delta + \gamma + \theta + \varepsilon \quad (2)$$

¹⁵ These examples are based on descriptive information on disorder events contained in the USD data, complemented with additional information sources for individual disorder events, as described in Section 4.3 and in Appendix E.

¹⁶ We thank one of the anonymous reviewers and the editor for suggesting mediation analysis. Our implementation of mediation analysis presented in this section follows closely Fagereng et al. (2021), who in turn base their mediation analysis on Heckman et al. (2013) and Heckman and Pinto, 2015.

¹⁷ For details see Appendix C.

where $Disorder_f$ is the potential intensity of social disorder for a city with flood exposure $Floods = f$, and π_f^m are the set of observed mediator variables. We include in π_f^m city population as our main mediator of interest. We also include GDP per capita, a democracy indicator and an indicator for national level armed conflict, to try to account for other potential mechanisms, including income effects and effects through institutional instability.¹⁸ The remaining variables on the right-hand side of Equation (2) are defined as in Equation (1).

Estimation of the mediation model proceeds in two steps. First, we estimate a model based on equation (2) with $Disorder$ as the outcome, and including both $Floods$ and the set of observable mediators π_f^m . The second step is to estimate separate regressions for each of the observed mediator variables, that is with π^m as dependent variable and X and $Floods$ as regressors. Results are reported in Table 3 and in Appendix Table (C.1).

In Columns 1 and 2 of Table 3, we show that floods significantly predict city population, while in column 3 we show that floods also predict disorder (replicating results in Table 2). Results in Column (4) show that floods, city population and national armed conflict are all significant predictors of the intensity of urban social disorder. Holding those factors constant, we do not find evidence of significant effects of income or democracy. We also estimate separately the effect of flood exposure on each of the other observed mediators, as reported in Appendix Table C.1. We find that flood exposure, as well as predicting city population, is also positively associated with national armed conflict, although the estimate is less precise ($p = 0.3$). Nevertheless in the

¹⁸ As discussed in Section 2, there are a number of mechanisms that could plausibly account for the positive association between floods and urban social disorders that we identify, including via: effects on conflict occurring elsewhere that spills over to urban areas; income effects; direct effects on food prices; effects on governance and institutions; or via the movement of displaced people from flooded areas to cities, resulting in unplanned city population growth. Mediation analysis for all these mechanisms in our context is challenging, given that social disorder is a highly complex phenomenon, while the scope of our study (89 countries over a 30-year period) makes gathering data on mediators that may be operating on local scales prohibitively costly. Our aim is not to identify every mechanism linking floods and disorder, but rather to provide a general sense of the relative magnitude of the estimated effects that are attributable to our primary mechanism (or mediating variable) of interest – i.e. city population.

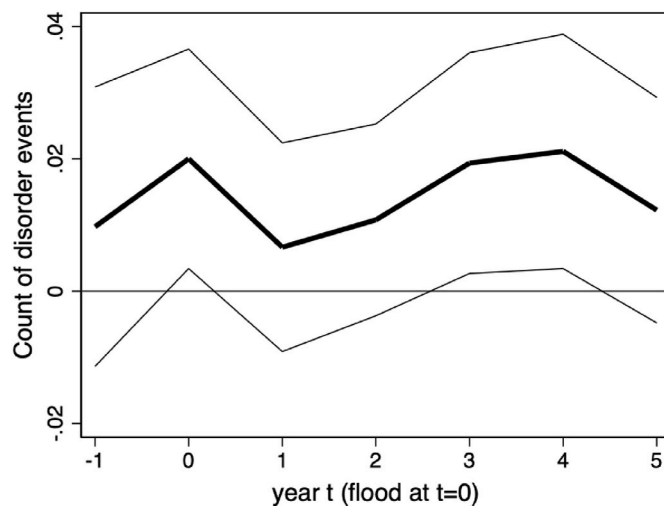


Fig. 4. Effect of floods on the intensity of urban disorder, different lag structures. *Notes:* This figure shows estimates based on Equation (1), including one lead and up to five lags. The regression includes time and city fixed effects, and the same set of controls as reported in Table 2 above. As the figure shows, there is no effect for disorder events before the floods (at $t-1$), as expected. Estimates are positive and significant for the contemporaneous effect, and again for the third and fourth lags (i.e., a longer-term effect).

following analysis we continue to consider this alternative mediator. Again, we do not find evidence that income and democracy are significantly affected by floods, and therefore do not consider these alternative mediators in the calculation of indirect effects.

Based on the results reported in Column (4) of Table 3, we calculate a total average treatment effect of a 29% increase in the incidence of disorder.¹⁹ Decomposing this average treatment effect, we find that the indirect effects arising from changes in the observed mediators account for about 18% of the average treatment effect of higher flood exposure. City population is the most important mediator variable, accounting for 71% of the indirect effect.²⁰ The magnitude of the estimated indirect effect via city population is a 3.8% increase in the incidence of disorder for “treated” cities. While this may seem modest in scale, the estimated effect increases substantially if we allow for cumulative effects over time. With five lags of floods exposure “treatment” and changes in city population included in Equation (2), the mediated effect via city population is a 12% increase in the incidence of disorder.²¹

4.2.1. 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 in the intensity of social disorder in cities. And this seems to happen, at least in part, 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. Floods are precisely a clear push

Table 3
The role of city population.

	(1)	(2)	(3)	(4)	(5)
	City pop	City pop	Events per million	Events per million	Events per million
	<i>Contemp.</i>	<i>Cumulative</i>	<i>Contemp.</i>		<i>Cumulative</i>
Floods	0.003*** (0.001)	0.013*** (0.004)	0.030*** (0.008)	0.023*** (0.008)	0.074*** (0.025)
City population				0.818*** (0.286)	0.665** (0.306)
Controls	YES	YES	YES	YES	YES
City and year fixed effects	YES	YES	YES	YES	YES
Observations	3030	2426	2746	2746	2377
No. of cities	101	99	98	98	97

Note: Floods is measured using the log of population exposed (weighted by distance). City population (in logs). Columns 1 and 2 estimated by OLS, with standard errors clustered by city. Columns 3–5 are estimated by Negative Binomial, with robust standard errors (in parenthesis) bootstrapped by the Jackknife method. In columns 2 and 5 the reported coefficients represent the cumulative effects of combining contemporaneous plus five lags of each explanatory variable. All regressions include city and time fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 (CFA) implemented by means of a Two-Stage Residual Inclusion (2SRI). 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).²² Appendix D provides formalization of the rationale behind the CFA.²³

Results for our annual data are presented in Table 4, while results aggregating over 5-year periods are presented in Table D.1 in Appendix D. Column 1 in Table 4 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

¹⁹ The “treatment” here, following Fagereng et al. (2021), compares values of our flood exposure variable at the 75th and 25th percentiles (9.88 and 0, respectively).

²⁰ Detail on the mediation analysis, including calculation of the estimated effects, is included in Appendix C.

²¹ The stronger effects are accounted for by the substantially larger cumulative coefficient on floods (including up to five lags) with city population as the outcome, as reported in column 2 of Table 3.

²² 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).

²³ 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; Wooldridge 2010). Also see Terza et al. (2008), for a good explanation of 2and Castells-Quintana and Royuela, 2017, for recent papers relying on 2SRI.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	City Pop	City Pop	Events per million	Events per million	Events per million	Events per million
Floods	0.002*** (0.001)					
Total Population	0.976*** (0.161)					
Economic Growth		0.002 (0.005)				
Sanitation		0.008*** (0.003)				
<i>Push-driven city growth</i>			0.772*** (0.313)		0.731** (0.313)	
<i>Pull-driven city growth</i>				0.782 (1.423)	0.637 (1.462)	
City population						1.016*** (0.242)
<i>Residuals from Column 1</i>						−0.535*** (0.167)
City Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	2667	1239	2637	1208	1208	2637
No. of cities	89	83	88	75	75	88

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 (per million). Floods is measured using the log of population exposed (weighted by distance). All regressions include city fixed effects and time-period fixed effects. Results presented in this table use the version of the data based on the largest city in each country only, given constraints on the availability of city level data for pull-factors. 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.

access to sanitation facilities as a proxy for public service provision.²⁴ In Columns 3–5, we show the effect of these different types of city growth on the count of disorder events. The results show contrasting estimates, 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 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. Here the results show a stark contrast, with a highly positive and significant coefficient for city size, and a negative and highly 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 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).²⁵

4.3. Results by type and motive of disorder

Results presented up to this point have been based on the count of events observed in the USD data for a given city (per million inhabitants), regardless of the nature of those disorder events. The USD data include a wide range of different events, such as riots, demonstrations and armed conflict. Given our primary interest in the effects of population displacement to cities on social disorder, in this section we restrict our attention to events classified only as riots or demonstrations

in the USD data. While flooding might plausibly be related to armed conflict events in urban areas, we believe that the mechanism behind this relationship is not mainly driven by congestion effects related to population pressures, which is our primary mechanism of interest.

We further review information on each of the 2695 events classified as either riots or demonstrations in the USD dataset that occurred during our sample period, to identify the motive of the tensions leading to disorder. After our search, we identify the motivation of 1123 events. The rest was classified as unidentified as we could not identify clearly the ultimate motivation behind the event. This procedure draws primarily on the qualitative (descriptive) information about the events contained in the USD data, supplemented by additional data searches using newspaper archives and policy reports as detailed in Appendix E.²⁶ Specifically, we classify each event into two broad categories, according to the motive of the tensions leading to disorder: First, related to our hypothesis, we identify disorder events related to public good provision, prices and wages. Examples of events in this grouping include disorders that occurred in Bangladesh in 2008, Morocco 1980, Nepal 1992 and Pakistan 2001 (as detailed in Appendix E). Second, a complementary group that includes disorder events related to (international) sanctions, ethnicity/race and religion, international migration and corruption. Summary statistics for this new classification of events is included in Table E.1 in Appendix E.

Events related to public good provision, prices and wages represent more than 55% of the riot and disorder events in the USD data that occurred during our sample period, and which we were able to classify by motivation. These are also the events where the effects of population displacement are most likely to be manifested (according to insights in Section 2). The (unplanned) displacement of population into cities can lead to congestion effects there. First, putting pressure in the access to urban public goods. Also, increasing the demand for several basic goods and services, leading, for instance, to a potential increase in food prices (a demand-side effect; there may also be supply side effects on food prices if food production in rural areas is directly affected by flooding). Finally, increasing the supply of labour in urban areas, especially low

²⁴ 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). Because of limited data at the city level for this variable, the results in Table 4 restrict the sample to just the largest city in each country. Equivalent results for all cities are reported in Table D.2 in Appendix D. Results are qualitatively unchanged.

²⁵ 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 5. 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 socioeconomic outcomes.

²⁶ Appendix E gives more information on the methodology implemented for the classification, definitions and examples of disorders in each category.

skilled labour, leading to more intense competition over jobs and potentially driving wages down.

To get an insight into the urban disorders related to public good provision, wages and prices, we look at two examples in our data. The first takes place in 2007 in Rangoon, Myanmar, where the police arrested some protesters following a public demonstration. The protesters were voicing concerns over commodity prices, health care, education and the unreliability of power supplies. This was partially the result of the cyclone *Akash* that affected an important part of the country and forcing many people to move. Similarly, in 2008 in Bangladesh, intense flooding in the rural areas nearby the capital destroyed harvests and displaced hundreds of families. Soon after, in June, garment workers in the central town of Savar, part of greater Dhaka, held strikes protesting about rising food prices, low wages and poor living conditions.

Table 5 presents results from estimating Equations (1) and (2), but now separating disorders according to the type and motive, as discussed. We start by taking the sub-set of events in the USD data that are labelled as riots or demonstrations. We find a positive albeit imprecisely estimated association between floods and the intensity of these disorder events, as reported in Column (1). However, even restricting our attention to riots and demonstrations, the data still includes a wide range of different disorder events, some of which are unlikely to be influenced by population displacement to cities (our main mechanism of interest). In Columns 2 and 3, we report estimates of Equation (1) for a partition of the riots and demonstrations events according to our classification by motive of disorder described previously. The results show a clear contrast in the effects of floods on disorder related to public service provision, prices and wages (Column 2), compared with disorder events arising from other motivations (Column 3), in line with our expectations.

Finally, we repeat the simple mediation analysis described in the previous section, by estimating versions of Equation (2) on these subsets of the USD data. Our expectation here is that if anything the mediated effect via city population should be more relevant for these types of disorder events. Results are reported in Columns (4) and (5) of Table 5, and in Fig. 5. In both cases, we find that the indirect effects arising from changes in the observed mediators now account for about a

third of the average treatment effect of higher flood exposure (38% in the case of riots and demonstrations, and 31% in the case of events related to public good provision, prices and wages).²⁷ Changes in city population is again the most important mediator variable, accounting for 87% and 100% of the indirect effect, respectively. The magnitude of the estimated effects mediated via city population is also larger here than for the full sample of USD events. We estimate a 5% increase in the incidence of riots and demonstrations, and a 10% increase in the incidence of events related to public good provision, prices and wages, via the effects of floods on city population. As with the results reported in Section 4.2 for the full USD set of events, the estimated effects here are even stronger if we allow for cumulative effects over time; at 12% and 20% increases in the incidence of disorder, respectively.

5. Discussion and conclusions

In this paper, we studied the displacement of population into cities and urban social disorders. In particular, we tested the effect of people displaced by floods that occurred elsewhere in the same country on protests and riots, for a panel of large cities in developing countries. To estimate the effect of population displacement on urban social disorder, we exploited 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 tested this connection explicitly in a global panel of cities. Specifically, we found that exposure to flooding elsewhere in the country leads to increased intensity of urban social disorders in large cities.

The use of a simple mediation analysis approach enabled us to i) provide a general sense of the relative magnitude of the estimated effects that are attributable to our primary mechanism of interest – i.e. city population, and ii) show that these effects operate via city population and are strongest for particular types of disorder events. However, we recognized the existence of other potential mechanisms, which we were unable to measure in our data, that might explain some of the “direct” relationship between climate shocks and urban social disorders, such as scarcity of resources in rural areas that can trigger conflict. Future research, taking a narrower geographic scope and time period, could fruitfully attempt to quantify a broader range of potential mechanisms.

Furthermore, our evidence suggested that the effect of floods on urban disorder happens at least in part through the displacement of population, and the “push” of people into cities. By disentangling push vs pull-driven city growth, our findings also helped to reconcile previously ambiguous results on the relationship between city population and urban social disorder. We showed dramatically contrasting results of these two different types of city growth, with push-driven city growth significantly increasing the incidence of urban disorders. Finally, by reviewing in detail descriptive information on each of the events included in the Urban Social Disorder dataset, we also found evidence that the effect of city growth on urban conflict was mainly associated with protests and riots related to public service provision, prices and wages, 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

Table 5
Results by motive of disorder.

	(1) Riots & Demos	(2) Pub good prov., prices & wages	(3) Other Riots & Demos	(4) Riots & Demos	(5) Pub good prov., prices & wages
Floods	0.017 (0.011)	0.029** (0.014)	−0.003 (0.046)	0.009 (0.011)	0.023 (0.014)
City Population				0.970*** (0.217)	1.491*** (0.421)
Controls	YES	YES	YES	YES	YES
City and year Fixed Effects	YES	YES	YES	YES	YES
Observations	2691	2384	2200	2691	2384
No. of cities	96	84	78	96	84

Notes: The outcome in Columns (1) and (4) is the count of disorder events labelled as Riots or Demonstrations in the USD data (per million inhabitants). The outcome in Columns (2) and (5) is the count of disorder events that we classify as either public good provision, prices or wages (as discussed in the text and in Appendix E), per million inhabitants. Column 3 includes all events we classified as other types of riots and demonstrations (See Appendix E). In Column (4) the outcome is the count of riots and disorders classified by other motivations, per million inhabitants. *Floods* is measured using the log of population exposed (weighted by distance). All regressions include city and time fixed effects. Bootstrap standard errors (by Jackknife method) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

²⁷ As the results in the table show, the flood exposure variable loses significance in Columns (4) and (5). If we were to treat these coefficients as indistinguishable from zero, the results would suggest that the effects of floods on disorder are *fully mediated* via the observed mediators in these cases. We adopt the conservative approach – relative to our hypothesis – of allowing for some (imprecisely estimated) direct effects of floods on these sub-sets of the disorders data, in interpreting these results.

(a) Share of the average treatment effect attributable to direct and indirect effects



(b) Share of indirect effect attributable to city population

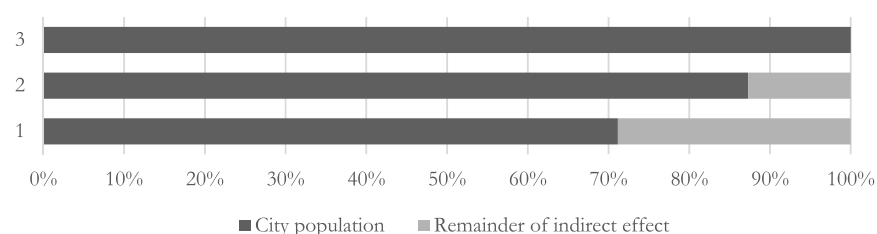


Fig. 5. Decomposing average treatment effect of flood exposure. *Notes:* These figures show decomposition of the direct and indirect effects (Panel (a)) and the share of the indirect effect attributable to our main mediator of interest, city population (Panel (b)), as discussed in the main text and in Appendix C. In both panels, the bottom row (1) refers to results for all disorder events, the middle row (2) refers to results for *Riots & Demonstrations* only, while the top row (3) refers to results for riots and demonstrations related to *public good provision, prices and wages* only. The legend entry for panel (a) here should be: "Indirect effect" (darker shade) "Direct effect" (lighter shade)

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. A sound design of development programs needs to properly account for the increasing interplay between deteriorating climatic conditions and demographic dynamics, and their socio-economic consequences in cities.

Author statement

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Data availability

I have added replication data in the Attach File step.

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Appendix A. Supplementary data

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