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Almer, Christian and Laurent-Lucchetti, Jérémy and oechslin, Manuel

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# Income Shocks and Social Unrest: Theory and Evidence*

**Christian Almer,**[†] University of Bern

**Jérémy Laurent-Lucchetti,**[‡] University of Bern

**Manuel Oechslin,**[§] University of Bern

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**Abstract**

Combining theoretical and empirical work, this paper explores the impact of economic shocks on the incidence of social unrest (i.e., mass demonstrations and violent riots) in autocracies. Our theory predicts negative economic shocks to boost unrest since – in bad times – fighting the regime to reduce the level of resource diversion becomes cheaper. Using a new dataset on political instability in Africa, our empirical analysis confirms this prediction. The instrumental variables estimates – which take into account the potential endogeneity of economic shocks – suggest a significant increase in the level of social unrest as a response to a decline in real per capita GDP.

**JEL classification:** D74, O17

**Keywords:** Conflict, social unrest, economic shocks

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[†]Department of Economics and Oeschger Center for Climate Change Research.

[‡]Department of Economics and Oeschger Center for Climate Change Research.

[§]World Trade Institute, Hallerstrasse 6, CH-3012 Bern, Switzerland; phone: +41 31 631 36 73; fax: +41 31 631 36 30, email: manuel.oechslin@wti.org.

# 1 Introduction

Over the past decade, understanding the determinants of civil conflict or civil war has become a central concern for academics and policy makers alike (see, e.g., Blattman and Miguel, 2010, for a recent overview).[1] So far, however, less attention has been paid to the roots of less intensive forms of conflicts such as mass demonstrations or violent riots. Yet, exploring the causes of such "smaller events" is important for a variety of reasons. For one, demonstrations and riots – even if they do not reach the intensity of civil conflicts or wars – disrupt economic activity and hence are an obstacle to economic development, particularly in poor places.[2] A second reason is that, according to conventional wisdom, civil conflicts or civil wars rarely start all of a sudden but are very often preceded by a chain of smaller events such as mass demonstrations and riots (see, e.g., Labrousse, 1969, for a detailed account of how the "food riots" of 1789, 1830 and 1848 in France turned into bigger conflicts). Thus, a better grasp of the forces behind such low-intensity conflicts may help us to better understand the emergence of truly disastrous events like full-blown civil wars.

In this paper, we make a first attempt at looking into the causes of mass demonstrations and violent riots in autocratic states. The paper offers two main contributions. *First*, we present a simple theoretical framework of social unrest (i.e., demonstrations or riots) from which we derive a set of predictions. *Second*, we use a new database on low-intensity conflicts in Sub-Saharan Africa to test these predictions, thereby carefully addressing causality issues. Our theoretical framework belongs to the class of rational conflict models in which social unrest may ensue between a constituted elite and the citizenry. We assume that the elite may try to appropriate resources from the citizenry while the latter can resort to social unrest, albeit at a cost, to oppose such a diversion. This setup gives rise to a simple Markovian equilibrium in which we observe social unrest only if there is a negative economic shock. A positive economic shocks, in contrast, has no impact whatsoever on the incidence of unrest. The intuition is that the elite must set the level of diversion before the realization of the citizenry's income. If the elite expects the economy to remain in a "good" state, it opts for a high level since rioting or demonstrating is expensive if incomes (and hence the opportunity cost) are high. Yet, if incomes drop due to a "bad" economic shock, the cost of conflict goes down – and it becomes suddenly worthwhile for the citizenry to fight resource diversion.

In order to assess these predictions empirically, we use a new source of data, the Social

[1] According to the usual definition, civil conflicts are internal conflicts that cause at least 25 battle death in a single year while civil wars are bigger events that count more than 1000 battle death per year.

[2] For anecdotal evidence, see, e.g., an article in *The Economist* ("A cracked nation holds its breath", January 17, 2008) which describes how the riots that erupted in Kenya in late 2007 imperiled the country's economy.

Conflict in Africa Database (SCAD). SCAD provides data on various forms of social conflict, among them demonstrations and riots, which usually cause only a "low" number of casualties and hence are not covered in datasets on civil conflict or war.[3] We further assemble data on natural weather variation to address the endogeneity of economic variables to conflict. According to Miguel et al. (2004), natural weather variation is likely to be an important source of income volatility in Sub-Saharan Africa as many countries heavily depend on agricultural production and only a tiny share of the cropland is irrigated. At the same time, weather variations are truly exogenous to human behavior and should therefore be independent of social conflicts. We thus introduce weather variations[4] as external instruments for GDP per capita (p.c.) in our estimation. However, we confirm previous results by Miguel and Satyanath (2011) that show little influence of weather variation on GDP p.c., especially after 2000. We therefore increase the relevance of our instruments by additionally including the (lagged) population growth rate as well as the GDP p.c. growth rate of important trading partners. These variables are usual candidates in the literature as instruments for the GDP p.c. (see, e.g., Baudry and Collard, 2006) or for foreign aid (Ree and Nillesen, 2009).

The results for all specifications under consideration are robust and show the predicted patterns. In particular, we find a statistically significant negative impact of GDP p.c. changes on the contemporaneous incidence of demonstrations and riots. This holds for all specifications, and the parameter estimates remain statistically significant after controlling for endogeneity. We even see a tendency towards bigger effects when using instrumental variables (IV). In particular, the IV estimates show that a contraction of the GDP p.c. of one standard deviation (6.8%) leads to about 1.5 additional instances of social unrest in the average Sub-Saharan country. Moreover, when controlling separately for negative and positive GDP p.c. shocks, we find that the relationship between income changes and the incidence of conflict is entirely driven by the negative shocks. Positive income shocks, as predicted by our simple theory, do not appear to have any systematic effect on the frequency of demonstrations and riots.

By emphasizing that negative economic shocks may spark conflict, our theory is related to models of civil war or political transitions. For instance, in the contest models proposed by Chassang and Padro-i-Miquel (2009, 2010) negative transitory shocks decrease the immediate cost of fighting – but not the discounted present value of victory. The model thus predicts that groups fight over power after a negative shock since they have less to lose than in periods

[3] In our country sample, the average number of casualties per incident varies across conflict categories and ranges from 0.7 (organized demonstration) to 5.5 (spontaneous violent riot).

[4] Kudamatsu et al. (2011) point out that there may be a direct effect of specific weather conditions on social unrest. We therefore control for potentially extreme weather events like heat waves, droughts, storms, and floods to rule out direct effects.

where generating output is more rewarding. Similarly, in Acemoglu and Robinson's (2001) theory of political change, negative economic shocks may induce democratization because – in bad times – fighting the autocratic regime is relatively cheap. As result, such regimes might be forced to make concessions when a negative shock hits.[5]

In other dimensions, however, there are stark differences. Our theory does not seek to explain big events like civil wars or democratic transitions. We rather explore the occurrence of smaller incidents like mass demonstrations or riots which may be sparked spontaneously by bad economic shocks. Therefore, our model does not rely on competing groups of about the same strength (as is usual in the literature) but rather assumes an asymmetric distribution of power. In the present framework, the maximum that can be achieved by rioting is to obtain immediate relief through a temporary reduction in resource diversion; a change in the balance of power, on the other hand, is out of reach. As a result, the elite's response to unrest is not large-scale violence but rather taking measures to alleviate economic distress. This focus on the immediate effects of economic shocks is also reflected in our empirical analysis which looks at the contemporaneous association between changes in the GDP p.c. and the incidence of social conflict. In contrast, the empirical work focusing on bigger events (e.g., Collier and Hoeffler, 2002; Miguel et al., 2004; Brückner and Ciccone, 2011) relates economic shocks to subsequent outbreaks of civil war or political transitions.

Finally, note that our theory does not only well in terms of explaining the empirical evidence on the incidence of social unrest. It is also consistent with how African governments responded to a recent series of riots. As described by Berazneva and Lee (2011), 14 African countries experienced severe rioting due to soaring food prices (and hence declining real incomes) in the 2007-2008 period. In most of these 14 countries, the government responded by taking measures which dampened the fall in real incomes (e.g., by reducing duties on food imports). This is exactly what the present theory would predict: In order to prevent the riots from going on indefinitely, the elite does not primarily resort to violence but reduces the diversion of resources and hence limits the fall in the citizenry's real income.

The rest of the paper unfolds as follows. The upcoming section lays out the simple theoretical model while Section 3 presents the econometric approach and the empirical results. In Section 4, we discusses some policy implications and outline a future research agenda.

[5] In Besley and Persson (2008), positive economic shocks (in the form of higher resource rents that accrue to the government) may lead to civil war because they increase the expected gains from fighting for power. Similarly, in Oechslin (2010), it is an increase in government-controlled rents that may destabilize the incumbent regime.

# 2 The Model

## 2.1 Assumptions

**Agents and preferences.** We focus on an infinite-horizon economy that consists of two players, the elite ($E$) and the citizenry ($N$). The preferences of both players are given by

$$v_{i,t} = E_t \left\{ \sum_{s=0}^{\infty} \beta_i^s u_i(C_{i,t+s}) \right\}, \tag{1}$$

where $u_i$ denotes the concave and non-decreasing instantaneous utility function of player $i \in \{E, N\}$, $C_{i,t}$ refers to consumption of the unique (non-storable) good in period $t$ and $0 < \beta_i < 1$ is the discount factor.

**Endowments.** The consumption good is produced by the citizenry only. The output in any given period $t$ is either high ($h$) or low ($l$), $Y_t \in \{Y^l, Y^h\}$, where $Y^h = \lambda Y^l$ and $\lambda \geq 1$. Changes in output between two consecutive periods are exogenous. More specifically, we assume that $Y_t = Y_{t-1}$ with probability $q$ and $Y_t \neq Y_{t-1}$ with probability $1 - q$. Obviously, $q$ is a measure of the persistence in output, and we impose $1 \geq q \geq 1 - 1/\lambda$. This assumption, consistent with observations, rules out that dramatic shifts in output happen too frequently. Intuitively, it requires an event that leads to a sharp reduction in output to be more persistent than an event leading to just a mild drop.

The elite is endowed with the power to appropriate part of the output generated by the citizenry. The magnitude of the desired resource appropriation is denoted by $T_t$. Whether or not the elite is in fact able to enforce the desired appropriation level depends on whether the citizenry will revolt, ($R_t = 1$), or not ($R_t = 0$). In the former case, the elite actually gets $T_t$, whereas in the latter case it cannot appropriate anything. Thus, we have

$$C_{E,t} = T_t(1 - R_t). \tag{2}$$

Note further that $T$ must be determined one period in advance. This means that, for instance, $T_t$ has to be set in period $t - 1$. A complete timing of events is given below.

A natural way to look at the elite is to think that it is in control of the government and hence can somehow extract resources from the private sector of the economy. Yet, changes in the level of extraction cannot be implemented immediately but require some time (e.g., because of necessary changes in extractive institutions).

**Social unrest.** As mentioned above, the citizenry can avoid resource appropriation by standing up against the elite (e.g., by revolting). However, staging a revolt is associated with a cost that is given by a fraction $\phi$ of the current output. Thus, the citizenry's level of consumption is given by

$$C_{N,t} = (1 - R_t)(Y_t - T_t) + R_t(1 - \phi)Y_t. \tag{3}$$

**Equilibrium concept and time line.** The focus is on the (pure strategy) Markov Perfect Equilibrium (MPE), where strategies depend only on payoff-relevant states of the system.[6] In the present setup, the state of the system is represented by the desired level of resource extraction, $T_t$, and the output, $Y_t \in \{Y^l, Y^h\}$.

The timing of events is as follows. First, all agents observe $T_t$ and $Y_t$. Second, the elite sets the desired level of resource extraction, $T_{t+1}$, for the following period. Third, the citizenry decides whether or not to revolt, $R_t \in \{0, 1\}$. Finally, all decisions are implemented, consumption takes place, and the period ends.

## 2.2 Analysis

**Decision on $R$.** It is convenient to look first at the citizenry's decision on whether or not to revolt. Since the citizenry's decision in a given period has neither implications for subsequent decisions nor for the course of the state variables, the maximization of lifetime utility (1) is achieved by maximizing current consumption (3) in every single period. In this regard, it is straightforward to verify that $R_t = 0$ gives the highest level of consumption, and thus utility, if and only if $T_t \leq \phi Y_t$. As a result, the maximum level of resource extraction that just avoids a revolt, $\widehat{T}_t$, is given by

$$\widehat{T}_t = \begin{cases} \widehat{T}^h = \phi Y^h & : \quad Y_t = Y^h \\ \widehat{T}^l = \phi Y^l & : \quad Y_t = Y^l \end{cases} .$$

Put differently, the citizenry opts for $R_t = 1$ if and only if the desired level of resource extraction, $T_t$, happens to exceed the critical threshold $\widehat{T}_t$:

$$R_t(T_t, Y_t) = \begin{cases} 0 & : \quad T_t \leq \widehat{T}_t \\ 1 & : \quad T_t > \widehat{T}_t \end{cases} . \tag{4}$$

Note that $\widehat{T}_t$ is smaller when output is low. The reason is that the cost of revolting is proportional to $Y_t$ and hence is smaller in times of low economic activity. Thus, in these times,

[6] Abstracting from potentially complicated punishment strategies allows us to focus on sharp predictions easily transferable to an empirical setup. It is noteworthy, however, that simple punishment strategies such as "Tit-for-Tat" or "Trigger strategy" do not constitute proper Subgame Perfect Nash Equilibria of this game.

the benefit of fighting the government exceed the cost of revolting at lower threshold.

**Decision on $T$.** We now move one step backwards and look at the elite's decision on resource extraction. Obviously, when deciding on $T_{t+1}$ (in period $t$), the elite takes the citizenry's response in the following period into account. Doing so implies that the elite will either opt for $\widehat{T}^l$ or $\widehat{T}^h$: A level of $T_{t+1}$ below $\widehat{T}^l$ cannot be optimal since it could be increased to $\widehat{T}^l$ without inducing the risk of a revolt; a level in between $\widehat{T}^l$ and $\widehat{T}^h$ cannot be optimal either because $T_{t+1}$ could be raised to $\widehat{T}^h$ without increasing the probability of revolt; finally, a level above $\widehat{T}^h$ can be ruled out because it would lead to a revolt with certainty.

As a result, when deciding on $T_{t+1}$ at the beginning of period $t$, the elite can concentrate on the simple "binary" recursive problem

$$V^E(T_t, Y_t) = \max_{T_{t+1} \in \{\widehat{T}^l, \widehat{T}^h\}} \left\{ u_E(C_{E,t}) + \beta_E E_t \left[ V^E(T_{t+1}, Y_{t+1}) \right] \right\}, \tag{5}$$

where $V^E$ refers to the corresponding value function.

**Proposition 1** *Suppose that the citizenry's decision rule is given by (4). Then, if $q \geq u_E(\phi Y^l)/u_E(\phi Y^h)$,*

$$T_{t+1}(T_t, Y_t) = \begin{cases} \widehat{T}^h & : \quad Y_t = Y^h \\ \widehat{T}^l & : \quad Y_t = Y^l \end{cases} \tag{6}$$

*is the solution to the recursive problem (5). Otherwise,*

$$T_{t+1}(T_t, Y_t) = \begin{cases} \widehat{T}^l & : \quad Y_t = Y^h \\ \widehat{T}^l & : \quad Y_t = Y^l \end{cases} \tag{7}$$

*solves (5).*

**Proof.** See Appendix. ■

Thus, to summarize, the MPE in this economy is represented by the policy functions (4) and, depending on the persistence in output, (6) or (7).

## 2.3 Discussion

After having established the equilibrium, it remains to discuss the relationship between economic activity and revolting. By looking at the definition of $\widehat{T}_t$ and policy function (4), it becomes clear that – in any given period $t$ – there will not be a revolt if $T_t = \widehat{T}^l$; moreover, the citizenry stays calm as well if $T_t = \widehat{T}^h$ but $Y_t = Y^h$. The only constellation that actually gives rise to a revolt is $(T_t, Y_t) = (\widehat{T}^h, Y^l)$. Yet, when does this constellation emerge? It is easy to see that it requires $q \geq u_E(\phi Y^l)/u_E(\phi Y^h)$ and $Y_{t-1} = Y^h$ (so that $T_t = \widehat{T}^h$ according policy function 6), but also $Y_t = Y^l$. Put differently, the economy sees a revolt only if there is a fall in output:

$$R_t = 1 \Longrightarrow Y_t - Y_{t-1} < 0.$$

On the other hand, if there is no change in output, or even a positive one, riots do not occur.

The explanation of why there may be revolts in equilibrium is that the elite is prepared to take a "risk" if $q$ is relatively high. In this case, claiming $\widehat{T}^h$ (and receiving this amount with probability $q$) brings the elite a higher utility than getting $\widehat{T}^l$ with certainty. As a result, the economy sees a riot only in the event of an economic downturn.

# 3 Empirics

## 3.1 Data

The data we are using come from several sources. Information on social unrest in Africa stems from a new dataset provided by the SCAD project.[7] SCAD lists different types of social unrest starting from 1990 for all African countries with a population size of more than 1 million. Among other things, the dataset contains detailed information on the number of spontaneous and organized demonstrations and spontaneous and organized violent riots. We aggregate these numbers to find the total number of demonstrations, riots, and instances of social unrest in a given country and year. Real GDP p.c. and population data are taken from the World Development Indicators (WDI) provided by the World Bank.

In order to address the potential endogeneity of the GDP p.c. we included additional variables that serve together with population growth as instruments in later regressions. The climate variables for precipitation and temperature originate from the CRU 3.1 dataset provided by the climate research unit at the University of East Anglia. The CRU dataset is the standard data used among climate scientists and the IPCC.[8] The originally grid-based (0.5 to 0.5 degrees) and monthly data has been aggregated on country and year level in order to relate climatic information to economic shocks. More precisely, for each country we accounted for

[7] Available at: www.scaddata.org. For further information see (Hendrix and Salehyan, 2010)

[8] See $http://www.ipcc-data.org/obs/cru_climatologies.html$. The advantage of CRU over similar weatherdata like GPCP (NASA) or ERA (ECMWF) is due to the fact that it contains both precipitation and temperature data; has a relatively high resolution (0.5 to 0.5 degrees); goes back to the year 1901.

the type of land use in order to capture the effect of weather conditions on economic activity.[9] Data on natural disasters are taken from the EM-DAT database provided by the Centre for Research on the Epidemiology of Disasters (CRED) at the Université Catholique de Louvain. By using this information, we are able to control for severe weather events that may have a direct impact on social unrest and, if not taken into account, may cause problems when using weather conditions as an IV for the GDP p.c. (Kudamatsu et al., 2010). We discuss this issue in greater detail in the following section. Information for the most important trade partners (Ree and Nillesen, 2009) is taken from the Bilateral Trade (v2.01) dataset of the correlates of war project (COW) and the World Development Indicators (WDI).

Summary statistics for all variables can be found in Table 1.

Table 1: Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| unrest | 3.85 | 7.12 | 0 | 66 | 754 |
| demo | 2.28 | 3.86 | 0 | 34 | 754 |
| riot | 1.57 | 4 | 0 | 42 | 754 |
| GDP (FD) | 0.01 | 0.07 | -0.69 | 0.64 | 753 |
| pop | 162.64 | 225.06 | 8.64 | 1513.19 | 754 |
| prec | 86.08 | 43.41 | 14.38 | 230.54 | 754 |
| temp | 24.61 | 3.5 | 11.56 | 30.14 | 754 |
| flood | 0.58 | 0.94 | 0 | 7 | 754 |
| drought | 0.14 | 0.35 | 0 | 2 | 754 |
| storm | 0.13 | 0.47 | 0 | 4 | 754 |
| exttemp | 0.01 | 0.08 | 0 | 1 | 754 |
| top5 | 3.36 | 2.54 | -15.79 | 15.31 | 752 |

Note: unrest stands for the sum of all demonstrations (demo) and riots in a given country and year. $GDP(FD)$ stands for the first difference of real per capita GDP in logs as defined in the following section. $trade5$ stands for the average GDP per capita growth of the 5 most important trade partners. *pop* is population in 100,000. *temp* and *prec* are average yearly temperature and precipitation for a country controlling for irrelevant regions (see web-appendix). In addition, we use information on extreme weather events like the number of floods, storms, droughts, and heat waves (exttemp) in later regressions.

## 3.2 Econometric Approach

**Specifications.** In order to test our theoretical predictions, we use the change in the GDP p.c. from year $t-1$ to $t$ to model economic shocks.[10] Following the previous empirical literature on the topic, we do not include the level of the GDP p.c. as an explanatory variable as it is

[9] For more information on the data and the aggregation process see the web appendix available at: *http://staff.vwi.unibe.ch/almer/download/suapp.pdf*

[10] In particular, we are using the first difference of the GDP p.c. in logs – which, in turn, is the log approximation of the growth rate.

highly persistent and its use may cause problems due to non-stationarity (see, e.g., Brückner, 2011). The basic version of the model to be estimated is therefore the following:

$$S_{it} = \alpha + \beta Y_{it} + \mu_i + \gamma_t + \epsilon_{it}, \tag{8}$$

where $S$ stands for the level of social unrest (number of events in a given country $i$ and year $t$),[11] $Y$ for the change in log real GDP p.c. ($Y_{it} = logGDP_{it} - logGDP_{it-1}$), and $\mu$, $\gamma$, and $\epsilon$ stand for country-specific effects, year-specific effects and the error term, respectively. Moreover, in order to check for robustness, we also estimated several alternative specifications that can be found in Section 3.3 and in the appendix. These include using random trends/country-specific time trends ($\sum_i trend_t * \mu_i$) instead of year dummies $\gamma_t$ (as in Miguel et al., 2004) and a dynamic specification (Ciccone, 2011) of the form $S_{it} = \alpha + \beta_s S_{it-1} + \beta_y Y_{it} + \mu_i + \gamma_t + \epsilon_{i,t}$.

In order to check for potential mean reversion (see, e.g., Ciccone, 2011), we also use the percentage deviation to the moving average of the last 3 years of GDP p.c. as this smoothes the series.[12] Results can be found in Panel A of Table 5 in the appendix. Additionally, we estimate a conditional fixed effects poisson and negative binomial[13] model to account for the count data structure of the dependent variable, and present the results in Section 3.3. However, given the data structure of our panel ($N = 41, T = 20$) and the resulting incidental parameters problem for large $T$ (see, e.g., Fernandez-Val and Vella, 2011), we focus on linear specifications when accounting for potential endogeneity as it has been done in the existing literature (see, e.g., Miguel et al., 2004; Burke and Leigh, 2010; Brückner and Ciccone, 2011; or Brückner, 2011).

**Addressing endogeneity.** The main challenge when analyzing the causal effect of income shocks on the level of social unrest is to account for endogeneity of almost any kind. It may not only be that current and past incidences of social unrest affect income (reverse causation) but also that third factors influence both income and social unrest at the same time (omitted variable bias). The resulting biases would be incorporated in the parameter estimate for $\beta$ and therefore interfere with the true effect income shocks have on social unrest. In order to correct for potential endogeneity of income shocks in equation (8), we therefore apply IV and GMM estimation using different external and internal instruments.

[11] As a sensitivity check we estimated an alternative specification using the growth of social unrest relative to the country mean as the dependent variable. The reason is that countries may respond differently in terms of magnitude to a given income shock depending on their average level of social unrest or the size of the country. The reader can find the results in Panel B of Table 6 in the appendix. Results are globally robust to this alternative specification with slightly higher standard errors.

[12] The exact formula is $[Y_{it} - (1/3) * [Y_{it-3} + Y_{it-2} + Y_{it-1}]] \,/\, [(1/3) * [Y_{it-3} + Y_{it-2} + Y_{it-1}]]$.

[13] There is evidence for overdispersion in our data, see Table 1.

The internal instruments are based on the work by Arellano and Bond (1991), Arrellano (1995), and Blundell and Bond (1998), and the corresponding results can be found in Table 7 (columns 1-3) in the appendix. Moreover, we use several external instruments in order to maximize their relevance for the GDP p.c. and to be able to test the resulting overidentifying restrictions. Those instruments include precipitation, lagged population growth, and the GDP growth of the individual most important trade partners of country $i$ at year $t$.

According to Miguel et al. (2004), Brückner and Ciccone (2011), and Burke and Leigh (2009), variation in weather conditions is a very important determinant of income volatility in Sub-Saharan Africa as many countries heavily depend on agricultural production. Moreover, such variations are truly exogenous to human behavior and should therefore be independent of social conflicts. As a result, weather conditions are popular candidate instruments for GDP in many circumstances. However, Kudamatsu et al. (2010) argue that weather conditions may influence conflict not only through income but also through health conditions. In this case, weather related information might not be an adequate instrument for GDP p.c. To account for this potential problem, we include several indicators for extreme weather events like the number of extreme temperatures, droughts, storms, and floods in our equation of interest when using IVs. The idea is to avoid that our weather variables, e.g., through extreme events in the first stage regression, influence conflict in other ways than through GDP p.c. We therefore want to ensure that our instrumental variables reproduce "usual" variations of weather conditions. However, we confirm previous results by Miguel and Satyanath (2011) in finding that weather seems to be a rather poor instrument in terms of relevance.

In order to increase the relevance of our instruments, we additionally include lagged population growth and GDP p.c. growth of important trade partners. Population growth is known to be an important determinant of GDP growth (for recent examples, see, e.g., Galor and Weil, 2000; Baudry and Collard, 2006) and one of the rare components of any kind of country-level growth regression (Durlauf et al., 2005) that we expect to be independent of social unrest (especially for lagged population growth). We validate this assumption in Section 3.3 by means of a difference-in-Hansen test. The last candidate instruments originate from a literature on the effects of foreign aid on civil war where GDP p.c. growth of important trade partners is used as instrument for aid (Ree and Nillesen, 2009). We build on this literature and use GDP p.c. growth of important trade partners as instrument for changes in domestic GDP p.c. Again, we assume that trade partner $j$'s GDP growth rate is independent of social unrest in country $i$ but influences changes in the GDP p.c. in country $i$.

The first observation is that weather conditions constitute rather weak instruments for

GDP p.c changes (see also Miguel and Satyanath, 2011). In fact, precipitation turns out to be of relevance for GDP only after expanding the functional form, controlling for the type of land use, and accounting for lagged effects as done in column 4.[14] Moreover, we only find very little evidence for temperature to influence GDP in our dataset. In contrast, there is little doubt that the first lag of population growth[15] is important, especially in terms of relevance when explaining variations in GDP p.c., as can be seen by both the highly economically and statistically significant estimate (columns 5 and 7 of Table 2).[16] The average GDP p.c. growth of the 5 most important trade partners proofs to be a valid instrument (columns 6 and 7) but also has a rather small effect on the domestic GDP p.c.

### 3.3 Results

**Baseline estimation results.** The results for all specifications under consideration are robust and show the expected patterns. We find a negative and statistically significant impact of the first difference of real GDP p.c. (GDP (FD)) on the level of social unrest. This holds for all specifications including the basic linear (Panel A of Table 3), count data (Panel B), and dynamic models (columns 1-3 of Panel C) and all kinds of alternative specifications for GDP (in Table 5 in the appendix). Moreover, effects are robust for demonstrations (*demo*), riots (*riot*), and the sum of the two (*unrest*). The estimates range from -2 to -6. Similar results show up when using country-specific time trends instead of year dummies as done in columns 4-6 (Panel A of Table 3). In Panel B, the reader finds results for conditional fixed-effects (FE) poisson (columns 1-3) and negative binomial (4-6) models which account for the count data structure of the dependent variable. Although parameter estimates are smaller (especially for total unrest), they still show estimates of around -2 and are highly statistically significant. Finally, in columns 1-3 of Panel C, results for the linear dynamic panel estimates (bias-correction as proposed by, e.g., Kiviet, 1995 and Bruno, 2005 using system GMM in a first step) are shown. Again, although social unrest seems to be persistent, results remain robust and show the expected negative effect of GDP p.c.

In order to study the way how income shocks affect social unrest in greater detail, we need to discriminate between the different types of income shocks. In particular, it might be the case that a positive income shock ($Y_{it} > 0$) reduces social unrest or that a negative shock

[14] We tested numerous different specifications for the weather variables (and the remaining candidate instruments) including changes in climatic conditions (first-differences, growth, deviations from moving averages), lag structures, and nonlinearities.

[15] Results are almost identical when using contemporaneous population growth. However, in order preclude any correlation with the level of social unrest we prefer using the first lag.

[16] There is no evidence for lagged or nonlinear effects in case of population growth or GDP growth of trade partners.

Table 2: First-Stage Estimates

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| drought | -0.0101 | -0.0109 | -0.00868 | -0.00929 | -0.00920 | -0.0125 | -0.0133 |
| | (0.064) | (0.049) | (0.100) | (0.090) | (0.112) | (0.013) | (0.013) |
| storm | -0.00329 | -0.00336 | -0.00267 | -0.00271 | -0.00152 | -0.00485 | -0.00368 |
| | (0.475) | (0.469) | (0.576) | (0.559) | (0.736) | (0.251) | (0.361) |
| flood | 0.00599 | 0.00573 | 0.00532 | 0.00547 | 0.00497 | 0.00551 | 0.00509 |
| | (0.012) | (0.018) | (0.017) | (0.017) | (0.028) | (0.011) | (0.024) |
| exttemp | -0.138 | -0.135 | -0.139 | -0.132 | -0.122 | -0.138 | -0.120 |
| | (0.240) | (0.254) | (0.238) | (0.272) | (0.247) | (0.234) | (0.259) |
| prec | -0.0261 | 0.0188 | | | | | |
| | (0.164) | (0.899) | | | | | |
| temp | -0.294 | | 1.027 | | | | |
| | (0.134) | | (0.502) | | | | |
| L.prec | | -0.269 | | 2.328 | | | 1.955 |
| | | (0.076) | | (0.082) | | | (0.127) |
| prec2 | | -0.00429 | | | | | |
| | | (0.826) | | | | | |
| L.prec2 | | 0.0345 | | -0.638 | | | -0.538 |
| | | (0.081) | | (0.076) | | | (0.116) |
| L.temp | | | 0.445 | | | | |
| | | | (0.736) | | | | |
| temp2 | | | -0.215 | | | | |
| | | | (0.405) | | | | |
| L.temp2 | | | -0.0512 | | | | |
| | | | (0.829) | | | | |
| L.prec3 | | | | 0.0566 | | | 0.0479 |
| | | | | (0.073) | | | (0.109) |
| L.pop | | | | | 1.500 | | 1.476 |
| | | | | | (0.009) | | (0.007) |
| trade5 | | | | | | -0.00373 | -0.00316 |
| | | | | | | (0.003) | (0.008) |
| N | 753 | 753 | 753 | 753 | 753 | 752 | 752 |
| R2 | 0.131 | 0.135 | 0.130 | 0.147 | 0.194 | 0.143 | 0.225 |
| R2 adj. | 0.0499 | 0.0518 | 0.0462 | 0.0666 | 0.120 | 0.0643 | 0.149 |

Note: $p$-values in parentheses. All estimates are first stage estimates (GDP p.c. change as the dependent variable) of linear fixed-effects IV estimation using heteroscedasticity and autocorrelation robust (HAC) standard errors and small sample adjustments.

($Y_{it} < 0$) boosts unrest, or both. According to the prediction of our theoretical framework, we expect negative income shock to be the one that lead to a clear-cut positive effect on social unrest, whereas positive shocks are predicted to have no influence. In order to reveal potential heterogeneous effects, we estimated the basic model by including specific dummies derived from GDP p.c. (see columns 4-6 of Panel C of Table 3). In particular, we included three dummies for GDP p.c. shocks, where $GDP25$ reflects severe negative shocks (in terms of distribution in the data), GDP50 stands for moderate negative shocks, and $GDP75$ stands for exceptional positive shocks.[17] The resulting pattern is unambiguous. It turns out that especially severe negative income shocks increase the prevalence of social unrest, especially for riots with estimates ranging from 0.6 to 1.3.

**IV estimation results.** It has already been extensively discussed that the GDP p.c. may suffer from different types of endogeneity in the present setting. Therefore, we use several external instruments including precipitation, population growth, and economic conditions of important trade partners (estimates for internal instruments can be found in Table 7 in the appendix). Results can be found in Table 4. In line with what one would expect, standard errors increase compared to the benchmark results but the parameter estimates remain statistically significant, at least when we increase the relevance of our set of instruments. Moreover, we even find a tendency towards even more economically significant effects of GDP p.c. changes.

In Table 4, we further report several test statistics that are of importance when evaluating our IV estimates. First, we report the Kleibergen and Paap (2006) test of under-identification. There is evidence for the instruments to be of relevance if we can reject the Null of under-identification. Moreover, we report the Hansen (1982) test of over-identifying restrictions, where the Null of orthogonality of the joint instruments is of interest. Finally, we display the difference-in-Hansen test, or C-statistic, that allows us to check for the orthogonality of single components of the set of excluded instruments. What we can observe is additional evidence for the weakness of weather in our IV estimation. The Kleibergen and Paap (2006) test of under-identification does not reject the Null of under-identification when using only weather instruments (see column 1-3 of Panel A in Table 4). However, when using lagged population growth, GDP growth of important trade partners, or all instruments together, we are able to reject the Null. For the Hansen (1982) test of overidentifying restrictions, we never find evidence against the Null of the validity of the instruments for any specification. As one might suspect that lagged population growth is not fully exogenous in our setup, we additionally

[17] A detailed description of the formulas can be found in the notes of Table 3.

Table 3: Baseline Estimates

| Panel A | | | | | | |
|---|---|---|---|---|---|---|
| | unrest | demo | riot | unrest | demo | riot |
| GDP (FD) | -6.044 | -3.657 | -2.387 | -5.955 | -3.412 | -2.543 |
| | (0.003) | (0.012) | (0.010) | (0.002) | (0.017) | (0.001) |
| N | 753 | 753 | 753 | 753 | 753 | 753 |
| Time Effects | TD | TD | TD | RT | RT | RT |
| **Panel B** | | | | | | |
| | unrest | demo | riot | unrest | demo | riot |
| GDP (FD) | -2.256 | -2.071 | -2.594 | -1.963 | -2.111 | -2.038 |
| | (0.002) | (0.011) | (0.008) | (0.012) | (0.008) | (0.026) |
| N | 753 | 753 | 753 | 753 | 753 | 753 |
| Time Effects | TD | TD | TD | TD | TD | TD |
| **Panel C** | | | | | | |
| | unrest | demo | riot | unrest | demo | riot |
| GDP (FD) | -4.955 | -3.420 | -2.013 | | | |
| | (0.008) | (0.006) | (0.075) | | | |
| L.unrest | 0.643 | | | | | |
| | (0.000) | | | | | |
| L.demo | | 0.363 | | | | |
| | | (0.000) | | | | |
| L.riot | | | 0.650 | | | |
| | | | (0.000) | | | |
| GDP25 | | | | 1.322 | 0.738 | 0.584 |
| | | | | (0.062) | (0.119) | (0.033) |
| GDP50 | | | | -0.0979 | -0.0694 | -0.0285 |
| | | | | (0.891) | (0.855) | (0.950) |
| GDP75 | | | | -0.220 | -0.287 | 0.0664 |
| | | | | (0.643) | (0.413) | (0.793) |
| N | 714 | 714 | 714 | 753 | 753 | 753 |
| Time Effects | TD | TD | TD | TD | TD | TD |

Note: $p$-values in parentheses. **Panel A:** GDP (FD): First-Difference of real log GDP per capita. Estimates show linear fixed-effects (within) estimation using Driscoll-Kraay standard errors (Discroll and Kray, 1998). Discroll and Kraay propose standard errors that are robust to heteroscedasticity, autocorrelation and cross-sectional dependence. TD stand for year dummies and RT for random trends as used in Miguel et al. (2004). **Panel B:** Conditional Fixed-effects poisson (column 1-3) and negative binomial (column 4-6) estimation using bootstrapped (on clusters) standard errors with 100 repetitions. TD stand for year dummies. **Panel C:** For the dynamic specification (columns 1-3) a bias-correction procedure has been implemented with bootstrapped standard errors (50 repetitions) using system GMM as a first stage estimate (see Kviet, 1995, Bun et al. 2003 and Bruno, 2005). Columns 4-6 present linear fixed-effects estimates using dummies for specific intervals of GDP per capita change and Driscoll-Kraay standard errors. In particular: $GDP25 = 1[Y_{it} < percentile(25)]$, $GDP50 = 1[0 > Y_{it} > percentile(25)]$, and $GDP75 = 1[Y_{it} > percentile(75)]$. Hence, moderate positive changes in GDP per capita serve as benchmark.

report a difference-in-Hansen statistic to test for its orthogonality. By looking at the $p$-values displayed in columns 4-6 of Panel B in Table 4, we do not find any evidence against the validity of the instrument.

On a side note, we also find the suspected direct effects of extreme weather conditions on conflict (Kudamatsu et al., 2010). Especially floods, and to a lesser extend droughts, seem to influence both the GDP p.c. and social unrest (see Table 4).[18]

The parameter estimates for the difference in log GDP p.c. (GDP (FD)) in our IV estimations show a consistent general pattern. We do find consistently larger negative estimates[19] ranging between -5.7 (riots, significant at the 20% level), -14 (demonstrations, significant at the 10% level), and -21 (sum of both, significant at the 10% level). Note that the estimates we obtain when using weather conditions as instruments are close to the ones suspected to be endogenous. However, when we add lagged population growth and GDP p.c. growth of trade partners, the IV estimates become bigger. Recalling that in our setup weather conditions is not a strong instrument, a candidate explanation is that the IV estimates are biased toward the OLS estimates if the instrument is weak (see , e.g., Han and Hausmann, 2003). Alternatively, Maccini and Yang (2009) explain similar low coefficient estimates through the measurement error in rainfall: Classical measurement error in the instrument will lead to attenuated coefficient estimates.

# 4 Discussion and Conclusions

Mass demonstrations and violent riots are widespread forms of social unrest in developing countries. There is no doubt that such incidents disrupt commerce and – if recurring frequently – may even impede long-run economic growth. Guided by a simple theoretical framework, this paper explores the roots of social unrest in Africa. Exploiting a new dataset, our empirical analysis suggests that negative income shocks are an important driving force of demonstrations and riots. In particular, our instrumental variables estimates identify a negative relationship between the change in the GDP p.c. (from $t-1$ to $t$) and the contemporaneous incidence of social unrest. Interestingly, we further find that this negative relationship is mainly driven by economic downturns: While strong negative shocks increases the incidence of social unrest, positive changes in income do little to promote stability.

The apparent asymmetry in the impact of positive and negative shocks is a reason for

[18] The IV estimates are not driven by the inclusion of extreme weather events. The results are robust when these variables are excluded (see Table 6 in the appendix).

[19] Except for the cases where we use the internal instruments (Table 7) or the weather variables only. In these two cases, the estimates are in a similar range as the benchmark results in Table 3.

Table 4: IV Estimates

| Panel A | | | | | | |
|---|---|---|---|---|---|---|
| | unrest | demo | riot | unrest | demo | riot |
| GDP (FD) | -4.613 | -3.253 | -1.359 | -21.06 | -13.92 | -7.140 |
| | (0.701) | (0.702) | (0.804) | (0.084) | (0.060) | (0.174) |
| drought | -0.511 | -0.149 | -0.362 | -0.659 | -0.245 | -0.414 |
| | (0.213) | (0.555) | (0.116) | (0.112) | (0.344) | (0.070) |
| storm | 0.299 | 0.0161 | 0.283 | 0.251 | -0.0148 | 0.266 |
| | (0.499) | (0.957) | (0.210) | (0.565) | (0.959) | (0.235) |
| flood | 1.322 | 0.506 | 0.815 | 1.410 | 0.564 | 0.846 |
| | (0.004) | (0.003) | (0.010) | (0.002) | (0.001) | (0.008) |
| exttemp | 2.174 | -1.118 | 3.291 | -0.0697 | -2.573 | 2.503 |
| | (0.742) | (0.689) | (0.428) | (0.992) | (0.376) | (0.551) |
| N | 753 | 753 | 753 | 753 | 753 | 753 |
| F | 1.583 | 1.864 | 1.178 | 1.686 | 2.086 | 1.152 |
| R2 | 0.133 | 0.105 | 0.116 | 0.0922 | 0.0472 | 0.104 |
| Klei | 0.211 | 0.211 | 0.211 | 0.0380 | 0.0380 | 0.0380 |
| Hans | 0.221 | 0.629 | 0.146 | | | |
| Time Effects | TD | TD | TD | TD | TD | TD |
| Instruments | Clim | Clim | Clim | POP | POP | POP |
| Panel B | | | | | | |
| | unrest | demo | riot | unrest | demo | riot |
| GDP (FD) | -20.89 | -15.63 | -5.257 | -17.48 | -11.72 | -5.761 |
| | (0.415) | (0.270) | (0.719) | (0.076) | (0.053) | (0.176) |
| drought | -0.726 | -0.312 | -0.414 | -0.688 | -0.268 | -0.420 |
| | (0.096) | (0.222) | (0.114) | (0.093) | (0.288) | (0.067) |
| storm | 0.196 | -0.0615 | 0.258 | 0.212 | -0.0430 | 0.255 |
| | (0.660) | (0.835) | (0.266) | (0.627) | (0.883) | (0.258) |
| flood | 1.408 | 0.572 | 0.836 | 1.390 | 0.551 | 0.839 |
| | (0.001) | (0.001) | (0.007) | (0.002) | (0.001) | (0.008) |
| exttemp | -0.0813 | -2.832 | 2.751 | 0.387 | -2.295 | 2.682 |
| | (0.992) | (0.443) | (0.579) | (0.954) | (0.416) | (0.524) |
| N | 752 | 752 | 752 | 752 | 752 | 752 |
| F | 1.740 | 2.072 | 1.227 | 1.782 | 2.108 | 1.240 |
| R2 | 0.0951 | 0.0279 | 0.112 | 0.112 | 0.0731 | 0.111 |
| Klei | 0.00304 | 0.00304 | 0.00304 | 0.0391 | 0.0391 | 0.0391 |
| Hans | | | | 0.456 | 0.774 | 0.365 |
| CStat | | | | 0.634 | 0.610 | 0.760 |
| Time Effects | TD | TD | TD | TD | TD | TD |
| Instruments | Trade | Trade | Trade | All | All | All |

Note: $p$-values in parentheses. Estimates for linear fixed-effects IV estimation using HAC robust standard errors. $Klei$ reports p-values for the Kleibergen and Paap (2006) underidentification test, $Hans$ for the Hansen test of overidentifying restrictions, and $CStat$ for the C-statistic or Difference-in-Hansen test of orthogonality of lagged population growth (Baum et al., 2011). **Panel A:** Using only precipitation (Clim) as instrument (columns 1 - 3, see column 4 of Table 2). Using lagged population growth as instrument (columns 4 - 6). **Panel B:** Using GDP p.c. growth of important trade partners as instrument (columns 1 - 3). Using all instruments (columns 4 - 6, see column 7 in Table 2).

concern. It implies that a higher volatility in GDP p.c. growth (e.g., due to more volatile weather conditions or a higher incidence of income shocks affecting important trade partners) leads to more demonstrations and riots. So our empirical findings suggest that climate change, by promoting greater variability in weather conditions, is likely to increase the level of social unrest in Africa. As a result, at least via the social-unrest channel, climate change should be expected to reduce the region's growth prospects. This prediction, in turn, has a number of clear policy implications. First, it implies that governments should reinforce measures to alleviate the impact of exogenous shocks on domestic incomes. For instance, better irrigation of arable land would mitigate the negative impact of extreme weather events (like droughts) on agricultural production and hence incomes. Second, governments should do more to reduce the level of resource diversion in good times. If that were achieved, the probability that an economic downturn sparks social unrest would be lower.

By offering new theoretical insights and empirical results, the present paper gives also rise to a number of new questions that would be interesting to address. For instance, anecdotal evidence suggests that "bigger events" like civil conflict or regime change are often preceded by periods of social unrest (while, of course, not all periods of social unrest lead to civil conflict and regime change). So an obvious question would be whether we find such correlations in cross-country data. Similarly, it would be of obvious importance to have a model that would allow us to explore the circumstances under which social unrest is more or less likely to escalate into such bigger events. Addressing these questions would help to fill the void between research on social unrest and the literature on civil conflict or regime change. At the moment, we leave these questions to future research.

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# A Appendix

**Proof of proposition 1.** In a first step, note that the elite's decision on $T_{t+1}$ has no impact on $C_{E,t}$. The elite's current level of consumption (2) is determined by the two state variables, $T_t$ and $Y_t$, and the current decision by the citizenry, $R_t$ (which, in turn, is independent of $T_{t+1}$). Thus, the recursive problem (5) can be rewritten as

$$V^E(T_t, Y_t) = u_E(C_{E,t}) + \beta_E \max_{T_{t+1} \in \{\widehat{T}^l, \widehat{T}^h\}} \left\{ E_t \left[ V^E(T_{t+1}, Y_{t+1}) \right] \right\}. \tag{5'}$$

The next step is now to substitute for $V^E(T_{t+1}, Y_{t+1})$ in problem (5') using this recursive definition of $V^E$ for period $t+1$. This eventually gives us

$$V^E(T_t, Y_t) = u_E(C_{E,t}) + \beta_E \max_{T_{t+1} \in \{\widehat{T}^l, \widehat{T}^h\}} \left\{ E_t \left[ u_E(C_{E,t+1}) \right] + \beta_E E_t \left[ Z_{t+1} \right] \right\}, \tag{5''}$$

where

$$Z_{t+1} \equiv \max_{T_{t+2} \in \{\widehat{T}^l, \widehat{T}^h\}} \left\{ E_{t+1} \left[ V^E(T_{t+2}, Y_{t+2}) \right] \right\}.$$

We now establish that, depending on the persistence in output, either (6) or (7) constitutes the solution to the recursive problem (5"). Given that one of these policy functions is applied in all future periods, $Z_{t+1}$ is unaffected by the decision on $T_{t+1}$ and hence $E_t [Z_{t+1}]$ is viewed as a constant by the elite. So the elite simply chooses $T_{t+1}$ to maximize $E_t [u_E(C_{E,t+1})]$. Suppose first that $Y_t = Y^h$. Then, due to the law of motion of $Y$ and the citizenry's decision rule (4), the elite will choose $\widehat{T}^h$ only if $q u_E(\phi Y_h) \geq u_E(\phi Y_l)$, i.e., only if $q \geq u_E(\phi Y_l)/u_E(\phi Y_h)$. Otherwise, if $q < u_E(\phi Y_l)/u_E(\phi Y_h)$, the elite will opt for the low level of diversion, $\widehat{T}^l$.

Suppose now that $Y_t = Y^l$. Then, the elite will choose $\widehat{T}^l$ only if $u_E(\phi Y_l) \geq (1-q) u_E(\phi Y_h)$, i.e., only if $q \geq 1 - u_E(\phi Y_l)/u_E(\phi Y_h)$. It happens that this inequality always holds: By concavity of $u_E(\cdot)$, we have $\lambda u_E(\phi Y_l) \geq u_E(\lambda \phi Y_l)$ and hence $u_E(\phi Y_l)/u_E(\phi Y_h) \geq 1/\lambda$ (recall that $Y_h = \lambda Y_l$ by notation). But this entails $1 - u_E(\phi Y_l)/u_E(\phi Y_h) \leq 1 - 1/\lambda \leq q$ so that the elite always chooses $\widehat{T}^l$ when $Y_t = Y^l$. Thus, depending on whether $q$ is greater than or less than $u_E(\phi Y_l)/u_E(\phi Y_h)$, the elite's policy function is given by either (6) or (7).

## A.1 Tables

Table 5: Additional Estimates I

Panel A: Percentage Change to 3 Years Moving Average

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| MA GDP | -4.406 | -2.683 | -1.723 | -4.808 | -2.636 | -2.172 |
| | (0.008) | (0.016) | (0.027) | (0.005) | (0.015) | (0.006) |
| N | 753 | 753 | 753 | 753 | 753 | 753 |
| Time Effects | TD | TD | TD | RT | RT | RT |

Panel B: Including Lags

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| GDP (FD) | -5.949 | -3.644 | -2.305 | -5.685 | -3.252 | -2.433 |
| | (0.002) | (0.007) | (0.016) | (0.004) | (0.017) | (0.007) |
| GDP (FD), lag 1 | -3.061 | -2.027 | -1.033 | -3.700 | -2.167 | -1.533 |
| | (0.003) | (0.015) | (0.081) | (0.000) | (0.003) | (0.011) |
| GDP (FD), lag 2 | 0.853 | 1.084 | -0.231 | 0.267 | 1.014 | -0.747 |
| | (0.372) | (0.126) | (0.578) | (0.786) | (0.100) | (0.241) |
| N | 750 | 750 | 750 | 750 | 750 | 750 |
| Time Effects | TD | TD | TD | RT | RT | RT |

Panel C: Nonlinearities

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| GDP (FD) | -5.284 | -3.283 | -2.001 | -5.372 | -3.063 | -2.308 |
| | (0.010) | (0.026) | (0.021) | (0.005) | (0.023) | (0.002) |
| GDP (FD), squared | 5.786 | 2.844 | 2.942 | 5.468 | 3.270 | 2.199 |
| | (0.197) | (0.327) | (0.153) | (0.015) | (0.128) | (0.023) |
| N | 753 | 753 | 753 | 753 | 753 | 753 |
| Time Effects | TD | TD | TD | RT | RT | RT |

Note: $p$-values in parentheses. Linear fixed-effects estimation using Driscoll-Kraay standard errors (Discroll and Kraay, 1998). **Panel A:** MA GDP stands for the percentage deviation of the change of GDP p.c. (GDP (FD)) from its moving average of the preceding three years. **Panel B:** Including lags 1 and 2 of GDP (FD). **Panel C:** Including GDP (FD) squared.

Table 6: Additional Estimates II

Panel A: IV estimates using alternative sets of instruments

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| GDP (FD) | -19.90 | -12.81 | -7.089 | -17.06 | -10.80 | -6.267 |
| | (0.058) | (0.045) | (0.119) | (0.080) | (0.074) | (0.126) |
| N | 752 | 752 | 752 | 753 | 753 | 753 |
| F | 1.895 | 2.281 | 1.274 | 1.797 | 2.147 | 1.248 |
| R2 | 0.0461 | 0.0307 | 0.0391 | 0.0590 | 0.0496 | 0.0428 |
| Klei | 0.0123 | 0.0123 | 0.0123 | 0.142 | 0.142 | 0.142 |
| Hans | 0.840 | 0.737 | 0.978 | 0.251 | 0.596 | 0.181 |
| Cstat | 0.840 | 0.737 | 0.978 | 0.534 | 0.434 | 0.736 |
| Time Effects | TD | TD | TD | TD | TD | TD |
| Instruments | All | All | All | All | NoClim | NoClim |

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| GDP (FD) | -17.13 | -10.97 | -6.157 | -10.62 | -7.058 | -3.567 |
| | (0.065) | (0.056) | (0.118) | (0.399) | (0.394) | (0.554) |
| N | 752 | 752 | 752 | 752 | 752 | 752 |
| F | 1.895 | 2.232 | 1.305 | 1.891 | 2.115 | 1.394 |
| R2 | 0.0602 | 0.0499 | 0.0439 | 0.0809 | 0.0764 | 0.0517 |
| Klei | 0.0384 | 0.0384 | 0.0384 | 0.0199 | 0.0199 | 0.0199 |
| Hans | 0.337 | 0.681 | 0.266 | 0.203 | 0.535 | 0.154 |
| Cstat | 0.555 | 0.528 | 0.577 | 0.483 | 0.397 | 0.537 |
| Time Effects | TD | TD | TD | TD | TD | TD |
| Instruments | NoTrade | NoTrade | NoTrade | NoPop | NoPop | NoPop |

Panel B: Growth rates

| | unrest | demo | riot | unrest | demo | riot |
|---|---|---|---|---|---|---|
| GDP (FD) | -1.985 | -1.791 | -2.636 | -4.796 | -5.323 | -2.784 |
| | (0.000) | (0.005) | (0.015) | (0.140) | (0.087) | (0.503) |
| N | 753 | 753 | 753 | 752 | 752 | 752 |
| F | 10213.0 | 9893.7 | 402.3 | 4.361 | 3.914 | 2.417 |
| R2 | | | | 0.0594 | 0.0389 | 0.0374 |
| Klei | | | | 0.0384 | 0.0384 | 0.0384 |
| Hans | | | | 0.814 | 0.939 | 0.432 |
| Cstat | | | | 0.412 | 0.380 | 0.793 |

Note: $p$-values in parentheses. **Panel A:** Estimates for linear fixed-effects IV estimation using HAC robust standard errors. $Klei$ reports p-values for the Kleibergen and Paap (2006) underidentification test, $Hans$ for the Hansen test of overidentifying restrictions, and $CStat$ for the C-statistic or Difference-in-Hansen test of orthogonality of lagged population growth (Baum et al., 2007). Concerning the set of instruments: All represents all available instruments including precipitation, lagged population growth and per capita GDP growth of trade partners. Accordingly, NoClim means that precipitation has been excluded, etc.. **Panel B:** The dependent variable here is the growth rate of social unrest relative to the country mean. In particular, $(S_{it} - \overline{S}_i)/\overline{S}_i)$. Results show linear FE estimates using Driscoll-Kraay standard errors (columns 1-3) and IV estimates using HAC robust standard errors (columns 4-6). All estimates include year dummies. IV estimates use all available instruments (precipitation, growth of trade partners, and population growth).

Table 7: Additional Estimates III

| | GMM estimation | | | | | |
|---|---|---|---|---|---|---|
| | unrest | demo | riot | unrest | demo | riot |
| drought | -0.282 | 0.363 | -0.645 | -0.608 | -0.265 | -0.391 |
| | (0.751) | (0.513) | (0.194) | (0.124) | (0.271) | (0.085) |
| storm | 0.00337 | -0.224 | 0.227 | 0.203 | -0.0423 | 0.240 |
| | (0.999) | (0.806) | (0.844) | (0.641) | (0.885) | (0.283) |
| flood | 0.960 | 0.428 | 0.532 | 1.316 | 0.556 | 0.732 |
| | (0.113) | (0.234) | (0.108) | (0.003) | (0.001) | (0.015) |
| exttemp | 0.386 | -0.377 | 0.763 | -1.499 | -2.464 | 1.125 |
| | (0.855) | (0.754) | (0.564) | (0.812) | (0.367) | (0.774) |
| GDP (FD) | -3.903 | -2.496 | -1.407 | -16.97 | -12.22 | -5.429 |
| | (0.052) | (0.061) | (0.278) | (0.073) | (0.037) | (0.178) |
| N | 753 | 753 | 753 | 752 | 752 | 752 |
| F | | | | 1.963 | 2.349 | 1.199 |
| R2 | | | | 0.112 | 0.0683 | 0.107 |
| Klei | | | | 0.0391 | 0.0391 | 0.0391 |
| Hans | | | | 0.456 | 0.774 | 0.365 |
| Cstat | | | | 0.634 | 0.610 | 0.760 |
| Sargan | 0.8083 | 0.9590 | 0.5323 | | | |
| arm1 | 0.0000 | 0.0041 | 0.0032 | | | |
| arm2 | 0.3874 | 0.4059 | 0.9587 | | | |

Note: $p$-values in parentheses. Columns 1 -3 report system GMM estimates using robust standard errors and lags 1 and 2 as instruments for GDP in the difference equation (see Blundell, 1998). *Sargan*, and *arm* stand for p-values of the Sargan statistic and autocorrelation tests of order 1 and 2. Columns 4-6 report results for GMM estimation of the linear fixed effects model presented in table 4 using all external instruments. Time dummies (and a constant) have been included but omitted here.