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If climate change can trigger civil conflict, can good policy trigger peace? Empirical evidence from cross-country panel data

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**If Climate Change Can Trigger Civil
Conflict, Can Good Policy Trigger Peace?
Empirical Evidence from Cross-Country
Panel Data**

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Abstract

Based on the analysis of a new cross-country panel data from Africa and the Middle East for the time period between 1981 and 2015, we show that reductions in per capita income growth rate or domestic food production induced by climate variation significantly increase the probability of civil conflict. A 10% reduction in economic growth or domestic food production leads to a 1.25% and 1.59% increase in the likelihood of civil conflict, respectively. Furthermore, we identify a direct link of climate on the incidence of civil conflict. Additionally, the level of democracy and good governance are good control variables. Regarding the Syrian conflict, when considering 2010 data, the increase in temperature growth explains around 30% of falling income growth as well as 85% of the shrinking food production index and in this way contributed to the onset of war. We explain the probability of ongoing conflict by 43–56%. The two strongest factors explaining the conflict are lagged conflicts and economic development. Adequate economic policies that are able to accelerate economic development, play a role in peace, and avoiding new conflicts.

Keywords: Climate variation, economic growth rate, food production index, civil war

1 Introduction

Climate variability and change affect a country's economy and households through multiple channels. For example, an increase in temperature and changing rainfall patterns affect the agricultural output of irrigated crops. Rising sea level will result in the loss of land, landscape, and infrastructure. The frequent flooding and extreme drought will change hydropower generation, and frequent floods will also increase the demand for public investment in physical infrastructure (Breisinger et al., 2011; Zenghelis, 2006; Dasgupta et al., 2007; Garnaut, 2008; Yu et al., 2010). Researchers warn of disastrous consequences for countries where fresh water is scarce and whose economies depend on local agriculture, such as many in Sub-Saharan Africa (SSA). Those countries are more vulnerable to a changing climate, leading to large losses projected in their national output (Thurlow et al., 2009). Likewise, Breisinger et al. (2010) that many countries of the Arab world have additional declines in agricultural yields, resulting in negative effects in rural incomes and food security.

In this way, in addition to social and political tensions, climate change impacts conflict risks in direct and indirect ways. Directly, researchers argue that deviations from moderate temperatures and precipitation patterns increase the risk of conflict (Burke et al., 2015; Hendrix and Salehyan, 2012), while other studies have found that low or declining rainfall increases the risk of communal conflicts, such as Hindu–Muslim riots in India (Bohlken and Sergenti, 2010; Sarsons, 2011), and leads to leadership change (Burke et al., 2012; Dell et al., 2012).

Furthermore, there is a lot of research devoted to the indirect impact of climate change when new natural conditions effect negative consequences for food production and economic development and in this way increase conflict risks.¹ For example, some studies provide evidence on the effects of temperature and rainfall variations on economic growth and its relations to conflict. Evidence from the Philippines shows that rainfall has an effect on agriculture and is related to civil conflict, whereby an increase in agriculture production dampens conflict intensity (Croston et al., 2018). Blattman and Miguel (2010) identify, among the most robust findings in the literature, that economic shocks induced by climate change are strongly correlated with civil conflict, where negative rainfall shocks reduce economic growth and thereby increase conflict risk. Collier et al. (2003) pointed to a correlation between food insecurity and political conflict, claiming that both

¹Surely, the relationship between economic development (or food insecurity) and conflict is more complicated. While many studies suppose that food insecurity can be a cause of conflict, there are also studies suggesting that food insecurity can be strongly established as a consequence of conflict. It is more appropriate to regard both aspects in the way that economic conditions and conflict risks are referred to each other in a harmful cycle, a "circulus vitiosus": in the absence of appropriate political responses and equal opportunities for all population groups, climate change can induce economic shocks and increase local environmental problems. That finally implies political conflicts and civil war. In turn, civil wars amplify environmental and economic development problems, leading to poverty and hunger

are symptoms of low development. Food security has been also identified by Maystadt et al. (2014) to be key for a peaceful transition in the Arab world. Most types of political violence addressed in a paper by Brinkman and Hendrix (2011) are more prevalent in societies with higher levels of chronic food insecurity.

The most widely cited study of Miguel et al. (2004) is the cornerstone of existing literature on civil war (Collier and Hoeffler, 2005; Hegre and Sambanis, 2006; Collier et al., 2009; Miguel and Satyanath, 2011). The results of this paper provide that a positive growth rate of rainfall increases GDP growth and reduces conflict risks in the countries of Sub-Saharan Africa. Afterwards, based on this paper, Ciccone (2011) re-examined the relationship between civil conflict and weather variations using an extended database from Miguel and Satyanath (2011). He found no robust link between civil conflict and annual rainfall growth (or rainfall year levels). However, applying Ciccone’s approach, Miguel and Satyanath (2011) re-examined the results and found that the findings hold even using rainfall levels as instruments. The second important point of the paper of Miguel and Satyanath (2011) is that the relationship between rainfall and GDP growth is weaker after 2000, suggesting that alternative instruments are needed when investigating recent conflicts.

In this context, it is of particular interest to contribute first, to a better understanding of the complex interrelation between economic development (and food insecurity) and conflict risks. Second, the question that has not yet been fully addressed in the literature is, what is the role of economic policies in avoiding the outbreak of a new war in light of climate change, or in triggering peace?

Like Miguel et al. (2004), Ciccone (2011), and Miguel and Satyanath (2011), in this paper we investigate the impacts of climate variations on conflict risks both in direct and indirect ways (through economic growth), and we estimate models with country and time fixed effects by means of a two-stage approach. However, compared to the above-mentioned authors who use mainly panel data for Sub-Saharan Africa, we developed an empirical framework with (i) new cross-country panel data collected by ourselves. In this dataset, we combine the conflict data of Themnér et al. (2018) with other climate, economic, social, political, environmental, and demographic variables for 59 countries of Africa and the Middle East from 1981 to 2015, collected from different sources (such as World Bank, FAO of the United Nations, WTO, UNESCO, etc.) and described more detailed in our code-book. (ii) Our data sample includes many more variables which can be used as alternative instruments for explaining important conflicts. For example, in addition to GDP growth rate, we explicitly take food production index into account as the second important explanatory variable. Food production index appears to be a strong instrument for explaining conflict risks. (iii) Compared to previous literature, our research does not focus on the relationship between explanatory variables and civil

conflicts in African countries only, since the linkage between climate and conflict is not a phenomenon unique to Africa but rather can be explained as a phenomenon of low levels of economic development and high levels of agricultural dependence (Salehyan and Hendrix, 2011). (iv) Moreover, based on the results from the two-stage approach, our paper explicitly takes Syria into account as the most important conflict in the last decade, as it has caused the displacement of more than six million Syrian people.

We highlight the case of Syria, since this is the best instance of a conflict apparently arising from the interrelations between climate change, economic development, and political conflict. Syria is a country with relatively high income inequality.² Regarding food security, Syria is highly dependent on agriculture. Moreover, agriculture is a source of livelihood and economic growth in rural areas (Solh and Saxena, 2011). Between 2006 and 2011, Syria experienced a multiyear period of extreme drought that contributed to agricultural failures (Gleick, 2014), causing worrying tensions in local food prices. While some studies try to explain a civil conflict in Syria only by reference to political instability (Karimi and Shafaei, 2018) or increasing international food prices (Johnstone and Mazo, 2011), we assume that only a combination of environmental, social-cultural, and economic factors can possibly give us a complete illustration of the incidence of civil war in Syria. Particularly, by means of computing marginal and total effects, we provide empirical evidence for the extent to which each group of factors contributed to probability of civil war in Syria.

In this paper, we first give a short overview about the economic, social, and political conditions in the country in the time before the crisis exploded. Second, we explain the data and the methodological framework. Last, we present our empirical results and discuss them.

2 The crisis in Syria

From the 1980s onwards, there was a course of liberalization of the Syrian economy, and the process was accelerated with the ascent of Bashar al-Assad in 2000. Given the importance of the agricultural sector in general and the livestock sector especially, the government focused on the development of the animal sector so that the contribution of the agricultural sector to the Gross Domestic Product (GDP) in fixed price ranged between 24% and 27% in the early 2000s and decreased to 16% during the 2005–2010 (Bibi and Nabli, 2010). The situation in this important branch of the economy had become very serious when the 2006–2010 drought converged with a shift in government agricultural policy regarding subsidies for irrigation and fertilizers. The combining of the withdrawal

²For example, the Gini index of inequality for Syria increased from 33.7 in 1997 to 37.4 in 2004. Inequalities in economic development, education, and the use of resources are strongly aggravated between urban and rural populations (Bibi and Nabli, 2010).

of the subsidies with the low rainfall apparently reduced production significantly (Middleton et al., 2018). While Syria’s food security index had been steadily increasing from the index of 2.2 in 1961 to 8.0 in 2007 when the government was promoting irrigated agriculture (Aw-Hassan et al., 2014), in 2006 the government sold off its grain reserves to take advantage of high global prices. Thus, no reserves were available when the drought hit in 2007–2008 so that food security in the country was violated (Akhmedkhodjaeva, 2015). Furthermore, during the worst three-year drought, there was a large-scale migration mostly from rural farming areas to urban centers, where young people needed to enter a depressed job market (Selby et al., 2017; Solh, 2010; Kelley et al., 2015). According to FAO (March 2017b), around 7 million food-insecure people were in urgent need of assistance during war years in Syria.

With roughly 23.5 million citizens in 2010, Syria is a country with many diverse religious and ethnic backgrounds including Sunnis, Alawites, Christians, Kurds, Armenians, Assyrians, Druze, and Turkmenians (Van Dam, 2011). The Sunni majority (75%) had regrets about privileges that were granted to Alawite elites (Hinnebusch and Zintl, 2015). Moreover, the problem generated mistrust between diverse population groups because this tension could not be faced or dealt with openly (Hinnebusch and Zintl, 2015).

In addition to the above-mentioned agricultural, religious, and ethnic factors, the lack of government accountability³ and the dependence on petroleum rent played important roles in the political and economic crisis in Syria (Hinnebusch, 2012; Hinnebusch and Zintl, 2015). The budget was highly dependent upon petroleum rent, making the country vulnerable to rent declines. In addition, the spread of electronic media contributed to political mobilization when there were attempts to demonstrate against regimes in neighbouring countries (Hinnebusch, 2012; Howard and Hussain, 2011). A combination of these factors, at least to a certain extent, led to increased poverty, influencing political conflicts and finally escalating into armed conflict by June 2011 (Hinnebusch and Zintl, 2015).

2.1 Data and description of variables

Data on civil conflict

As in recent studies (Miguel et al., 2004; Miguel and Satyanath, 2011), for our conflict variables, we adopted the UCDP/PRIO Armed Conflict Dataset⁴ for countries in our sample. However, we included many more countries and years than the study of Miguel et al. (2004). Our sample contains data for 59 countries of the African continent and the Middle East from 1981 to 2015. While the conflict data include four types of conflicts (type 1, 2, 3, and 4), we focus on conflicts of type 3 and type 4 covering civil conflicts with

³Based on the Voice and Accountability index, Syria was ranked 187 out of 193 states during 1996 to 2014 (World Bank, 2017).

⁴We used the dataset of version V18.1, available on the website: <http://ucdp.uu.se/downloads/>.

and without intervention from other states on one or both sides, respectively. In this way, the conflicts of type 3 and type 4 indicate internal and internationalized internal conflict.

According to the data coding of Themnér et al. (2018) and in a similar manner to Miguel et al. (2004), we generate three dependent conflict variables (*any_prio*, *minor_prio*, and *war_prio*) by means of comparing the intensity level of conflicts. Minor conflict (*minor_prio*) means between 25 and 999 deaths in a given year, war (*war_prio*) implies at least 1,000 battle-related deaths in a given year, and any conflict (*any_prio*) contains the union of both kinds of incidences. In this way, based on the type and the intensity level of the conflict, all country-year observations (for country i and time t) are coded as ones, otherwise as zero. More details for the formulation of our variables are described in Appendix A attached to this research (Data Set Description), while detailed definitions of the types of conflict are available in the UCDP/PRIO Armed Conflict Dataset Codebook as described for example in Themnér et al. (2018), Gleditsch et al. (2002), Harbom et al. (2009), or in the dataset of Miguel et al. (2004).

Weather variables

To quantify the direct effects of climate change on conflict risks as well as the indirect impact of natural conditions on conflicts when affecting economic situation and food security, we collected different measures capturing exogenous variation in rainfall and temperatures (see data set description in Appendix A). The variables used in this paper are:

- The annual rainfall level (mm) is computed by adding up all of the monthly observations in a given year and its respective lags: *rainfall*, *rainfall_lag_1*, *rainfall_lag_2*
- A relative change in rainfall in a year related to the previous year is the principal measure of many above-mentioned studies:

$$gr_rainfall = (rainfall - rainfall_lag_1) / rainfall_lag_1$$
- The annual temperature (degrees Celsius) is computed by adding up all of the monthly observations in a given year divided by the number of months in that year, and its lags: *temp*, *temp_lag_1*, *temp_lag_2*.

Furthermore, we are interested in understanding whether rainfall level and precipitation growth rate are still important measures for conflict risks when regarding the total water availability in a country. For instance, a high level of precipitation might be a real problem for countries which frequently suffer from floods destroying infrastructures, but it might be no problem for countries with dry climate conditions. On the other hand, the extremely low level of rain availability might be a real challenge for regions with frequent drought and may pose no problem for regions in which water has been stored in the reservoirs in the past. Therefore, we computed interaction effects. We have taken Germany (with 727

mm annual precipitation) as a reference country with a peaceful situation and a sufficient level of precipitation in the last decade. Therefore, we computed dummy and interaction effects as follows:

- A dummy *low_rainfall_countr* is equal to 1 if the annual rainfall level in a country was lower than in Germany, otherwise 0;
- The interaction effect between the dummy *low_rainfall_countr* and the growth rate of rainfall is $inter_L_gr_rainfall = low_rainfall_countr \times gr_rainfall$;
- The interaction effect between the dummy *low_rainfall_countr* and rainfall level is $inter_L_rainfall = low_rainfall_countr \times rainfall$;

In the same way, we have gone forward with respect to countries with a high mean level of available water. These variables are described in the data set description (Appendix A); they didn't have a significant effect on conflict risks and therefore are not worth mentioning here.

Socio-economic variables

There are several sources which provide GDP per capita, but most of the time series data (such as the World Development Indicators source) are not complete for our sample of 59 countries from 1980 to 2015. However, we found that the database of UNSD (2020) was able to cover gaps over almost all countries and years. This database provides a complete and consistent set of GDP per capita time series from 1970 onwards of the main National Accounts data aggregated for all UN Member States and other territories in the world for which National Accounts information is available.

Overall, the main problem when creating one's own database is that different sources have various methodologies for measuring the same indicators. Therefore, in our database we adopted more as one indicator (for example, GDP per capita) measured in different ways, for example in current and constant prices (see Appendix A).

However, in this paper we present the results based on the following indicators:

- Measure of GDP per capita in constant price (US dollars), and its two lags from the source UNSD (2020): *gdp_c_con*, *gdp_c_con_lag_1*, *gdp_c_con_lag_2*;
- Relative changes in GDP per capita from the previous year and its lag:
 $gr_gdp_c_con = (gdp_c_con - gdp_c_con_lag_1) / gdp_c_con_lag_1$ and
 $gr_gdp_c_con_1 = (gdp_c_con_1 - gdp_c_con_lag_2) / gdp_c_con_lag_2$;
- Food production index is the aggregate volume of agricultural production for each year compared to the base period 2004–2006, covering food crops that are considered edible and that contain nutrients (Food and Agriculture Organization of the United Nations, 2016): *food_index*;

- Oil exporter status (% of merchandise exports) from World Bank (2016), and its lags: *oil_exp_wdi*, *oil_exp_wdi_lag_1*, *oil_exp_wdi_lag_2*;
- Relative changes in oil exporter status from the previous year: $gr_oil_exp_wdi = (oil_exp_wdi - oil_exp_wdi_lag_1) / (oil_exp_wdi_lag_1)$;
- Total merchandise trade of a country exports to the world in US dollars at current prices from The World Trade Organization (2016), and its lags: *trade_exports*, *trade_exports_lag_1*, *trade_exports_lag_2*;
- Changes in total merchandise trade of a country exported to the world in US dollars at current price from previous year:
 $gr_trade_exports = (trade_exports - trade_exports_lag_1) / (trade_exports_lag_1)$.
- Share of the urban population as a percent: *urban_pop*.

Fractionalization data

For measuring ethnic and religious fractionalization, we use the fractionalization index provided by Alesina et al. (2003), computed by the formula $FRAC_m = 1 - \sum_{i=k}^N S_{km}^2$, where S_{km} is the share of group k in country m . The variables for ethnic and religious fractionalization were disaggregated and combined from several sources (see more details in the code-book), but the primary source was Encyclopaedia Britannica (2001):

- Ethnic fractionalization: *ethnic*;
- Religious fractionalization: *religion*.

Political controls

- Type of political regime for each country on a range from -10 (full autocracy) to +10 (full democracy) named as Polity IV scores (Roser, 2019; Polity IV Project, 2013; Wimmer and Min, 2006): *polityiv*;
- Transformed Polity IV scores (*polity_iv*) on a positive range from 1 to 20, and its two lags: *polityiv_tr*, *polityiv_tr_lag_1*, *polityiv_tr_lag_2*;
- The variable constructed to measure the absolute strength of a political shock in a country in a year compared to the previous year:
 $strength_gr_polityiv = |polityiv_tr - polityiv_tr_lag_1|$, it dose not matter whether the shock was toward democracy or backward to autocracy;
- Voice and accountability indicator as percentile rank among all countries (ranges from 0=lowest to 100=highest rank), which reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, association, and a free media (World Bank, 2014): *accountab*.

Natural conditions

- *agri_land*: Agricultural land (% of land area) refers to the share of land area that is arable as defined by the FAO, under permanent crops, and under permanent pastures. Land abandoned as a result of shifting cultivation is excluded (World Bank, 2016).
- *arable_land*: Arable land in hectares per person.
- *area.km2*: Is the total area of a country in km².

Furthermore, based on the data of FAO (2017a), which are available for five-year periods from the 1980s for most countries in our sample, we generated the following variable for water use:

- *freshwater* is freshwater withdrawal as % of total renewable water resources.
- *agri_renew* is agricultural water withdrawal as % of total renewable water resources (%).
- *water_stress* is an aggregated indicator of freshwater withdrawal as a proportion of available freshwater resources. This indicator is also known as water withdrawal intensity.
- *wasser_total* is the annual level of freshwater withdrawal, calculated as an average over each decade (1980–1989, 1990–1999, 2000–2017), in 10⁹ m³/year.
- *water_1km2* is average annual level of freshwater withdrawal (calculated as an average over each decade) divided by country area as
 $water_1km2 = 10^6 \times wasser_total / area.km2$, in 10³ m³/km².

3 Empirical framework

In the two-stage approach, we capture direct and indirect effects of weather variation (rainfall and temperature) as well as other external shocks on the incidence of civil war. On the one hand, weather and environment variables can affect conflict probability through economic development, if (for example) strong rain destroys harvests and causes social tensions. Therefore, the *indirect impact* of environment variables will be considered in the first stage of the regression by means of instrumentalizing two variables describing economic situation, economic growth, and food production index. For example, Buhaug et al. (2015) revealed a robust link between weather patterns and food production across Sub-Saharan Africa and indicated that covering indirect and conditional effects of climate variability on collective political violence via food production shocks is very important. Moreover, investigating the political effects of domestic food production shocks is more relevant than studying social responses to food price changes.

On the other hand, we capture a *direct impact* of weather and environment variables on incidence probability. Additionally to instrumentalized variables of economic development, we take into account variables for environmental, ethnic, and political conditions in regressions of the second stage. Moreover, since experiencing conflict in the past may increase the probability of being in a conflict in the following year, we include the impact of lagged conflict as an explanatory variable on the incidence of civil conflict.

With the econometric software STATA, we have tested a wide range of methods: Generalized Method of Moments (GMM), a two-stage least squares method by instrumental variable estimator (IV-2SLS), as well as probit models. First, to take lagged conflict explicitly into account, we estimated our model with Dynamic Panel Data estimators (DPD) based on GMM, because this kind of model allows us to include one or more lagged dependent variables (Roodman, 2009; Arellano and Bover, 1995; Blundell and Bond, 1995). We applied an estimator of GMM introduced by Hansen (1982) and implemented by Roodman (2009) in the STATA package *xtabond2*. To ensure that the estimator is robust to heteroskedasticity, we used the option *robust* on the command *xtabond2*.

Second, we applied the IV-2SLS-method with package *ivreg2*. In this method, we excluded lagged dependent variables from regressions because this method doesn't control unobserved heteroskedasticity. We applied this method first of all for identifying strong instruments for endogenous variables of economic development in the first stage. Therefore, in this paper we focus on results for the two methods mentioned above.

Additionally to these two approaches, we also tried to estimate probit models. Unfortunately, probit models are not able to take into account lagged explanatory variables. Moreover, using probit models with endogenous variables may lead to inconsistency and even bias in the case of fixed effects (Greene, 2002; Arellano González, 2005). To ensure that the chosen instruments are strong enough for endogenous variables *gr_gdp* and

food_index, we do many statistical tests: First, we applied the IV-2SLS method and used the Sanderson-Windmeijer (SW) Chi-squared and F -statistics that test underidentification and weak identification of endogenous variables. The null hypotheses were rejected. The SW Chi-squared statistic⁵ equals 172.66 (p -value= 0.000) for GDP growth and 293.09 (p -value= 0.000) for the food index. SW F statistics account for 31.72 and 53.85 for both regressors, respectively—greater than recommend level of 10. Next, we test for overidentification by Hansen J-statistic after command *ivreg2*.⁶ The joint null hypothesis of the Hansen J-test that the instruments are valid instruments (i.e., they are uncorrelated with the error term) could not be rejected with the p -value 0.529. Furthermore, we controlled our sample with respect to heteroskedasticity with the Breusch-Pagan/Cook-Weisberg test: the null hypothesis that the error variance is constant was rejected with $\text{Prob} > \chi^2 = 0.000$, pointing to heteroskedasticity in our sample. In this context, since in IV-2SLS the heteroskedasticity problem may make our estimated coefficient less precise, we focus on the results from GMM estimation eliminating this problem. However, we will take into account the results from both methods.

3.1 Results from the first stage

In the first stage, two economic variables (economic growth rate and food index) for country i and year t will be instrumentalized by a vector of explanatory variables for weather and environment conditions (X'_{it}) including fixed effects. Similarly to Miguel et al. (2004), we included country fixed effects a_i to capture time-invariant country characteristics that may be related to civil conflict, as well as country-specific time trends $year_t$ to capture additional variation over time:

$$gr_gdp_{it} = a_i + bX'_{it} + d_i year_t + e_{it}, \quad (1)$$

$$food_index_{it} = a_i + bX'_{it} + d_i year_t + e_{it}, \quad (2)$$

where the error term e is allowed to be correlated across years for the same country. When searching for strong instruments, we applied many different variables available in our dataset. However, a constellation of explanatory variables presented in the following discussion provided statistically better results fitted by values of R^2 and the F -test. Moreover, we present only the results of those variables which have no multicollinearity problem. Furthermore, country and country specific time fixed effects were included for all countries and estimations. However, focusing on the Syrian conflict in this paper, in Table 1 we decided to include estimated coefficients only for four selected countries,

⁵SW Chi-squared was computed for $(L1 - K1 + 1)$ degrees of freedom where $L1$ is the number of excluded instruments and $K1$ is the number of endogenous regressors.

⁶Remark: the Hansen test was done after country fixed effects were removed from the equation because otherwise an estimated covariance matrix with dummy variables is not of full rank.

although all countries were included in the estimation. The countries are Syria, Turkey, Iraq, and Iran. Furthermore, we allowed ourselves to display some insignificant variables in the results table, because their impact is often discussed by other authors.

Although the food index is positively correlated with economic growth rate (0.12), it is affected by the same variables differently. In Table 1, in the OLS regression the given explanatory variables explained the food index better than economic growth (with R^2 equaling 0.87 versus 0.16). Overall, there are only a few variables that have a significant impact on GDP growth. From the first group of variables related to economic and agricultural factors, agricultural land and a relative change in trade exports enhance economic growth by 0.004** and 0.113***, respectively. However, arable land decreases GDP growth rate (-0.284*). This may be explained by the fact that a high share of crop items being less expensive than oil or even animal products may have a negative effect on their proportion in the total value of gross domestic product.

By contrast, the food index is negatively affected by a growth rate of trade exports (-0.016**), pointing out that more industrialized countries exporting industrial goods and oil give less support for agricultural branches and rely heavily on food imports (Maystadt et al., 2014). For example, in the Gulf countries, oil production is dominant at the expense of arable land and agricultural production, and simultaneously the highest share of total exports in Oman and Yemen is fish and fish products needing no arable land. Furthermore, agricultural and arable land raise the food index by 0.014*** and 0.481***, respectively. Furthermore, the share of urban population is positively related to the food index (0.005**). It seems that a higher share of urban population forces a higher food supply. This is because in higher urbanised countries, agricultural branches that are more intensified are able to provide relatively more food (Satterthwaite et al., 2010).

Regarding the second group of variables referring to environmental conditions, a change of one percentage point (1 pp) in temperature growth significantly reduces economic growth by 0.310 pp and food index by 0.227 pp. Considering the temperature increase in the last two decades, this is a huge effect. For example, while in the 2000s global mean temperature difference was around 0.6°C above pre-industrial levels (1850–1900), in 2019 this temperature change was already around $1.1 \pm 0.1^\circ\text{C}$ (World Meteorological Organization, 2019).

That means a near doubling of temperature growth, or a 100% increase over 20 years, calculated as:

$$\frac{\Delta t}{t} = \frac{\bar{t}_{2019-1900} - \bar{t}_{2000-1900}}{\bar{t}_{2000-1900}} = \frac{1.2 - 0.6}{0.6} = \frac{0.6}{0.6} = 1, \quad (3)$$

where \bar{t}_{y-1900} is an average temperature change between year y and 1900. We controlled for the average increase in temperature growth in our data. First, we observe a significant increase of the average temperature over all countries as well as in Syria. For example,

Table 1: First-stage results for economic growth rate and food index

| | (1) | | (2) | |
|-----------------------------|---------------------|---------|-------------------|---------|
| | <i>gr_gdp_c_usd</i> | | <i>food_index</i> | |
| <i>gr_trade_exports</i> | 0.113*** | (0.000) | -0.016** | (0.015) |
| <i>gr_oil_exp_wdi</i> | 0.000001 | (0.620) | -0.000002 | (0.289) |
| <i>agri_land</i> | 0.004** | (0.044) | 0.014*** | (0.000) |
| <i>arable_land</i> | -0.284* | (0.052) | 0.481*** | (0.000) |
| <i>urban_pop</i> | -0.002 | (0.490) | 0.005** | (0.016) |
| <i>gr_temp</i> | -0.310** | (0.032) | -0.227* | (0.056) |
| <i>gr_rainfall</i> | 0.047 | (0.251) | -0.012 | (0.715) |
| <i>rainfall</i> | -0.000004 | (0.933) | 0.00003 | (0.483) |
| <i>inter_L_gr_rainfall</i> | -0.068 | (0.110) | 0.003 | (0.927) |
| <i>inter_L_rainfall</i> | 0.0002** | (0.026) | 0.0001* | (0.091) |
| <i>water_stress</i> | -0.00002 | (0.869) | -0.001*** | (0.000) |
| <i>water_1km2</i> | 0.0002 | (0.877) | -0.0004 | (0.617) |
| <i>polityiv_tr</i> | -0.0004 | (0.785) | -0.008*** | (0.000) |
| <i>strength_gr_polityiv</i> | -0.007*** | (0.001) | -0.003 | (0.126) |
| <i>accountab</i> | 0.001 | (0.397) | 0.001 | (0.417) |
| <i>ethnic</i> | 0.019 | (0.922) | -0.303* | (0.058) |
| <i>religion</i> | -0.143 | (0.557) | 0.090 | (0.652) |
| <i>year_trend_TUR</i> | -0.001 | (0.822) | 0.019*** | (0.000) |
| <i>year_trend_SYR</i> | -0.002 | (0.431) | 0.020*** | (0.000) |
| <i>year_trend_IRQ</i> | 0.005* | (0.073) | 0.012*** | (0.000) |
| <i>year_trend_IRN</i> | 0.004 | (0.228) | 0.028*** | (0.000) |
| <i>dummy_country_TUR</i> | 0.125 | (0.244) | -0.088 | (0.315) |
| <i>dummy_country_SYR</i> | 0.101 | (0.459) | -0.518*** | (0.000) |
| <i>dummy_country_IRQ</i> | 0.270 | (0.175) | 0.611*** | (0.000) |
| <i>dummy_country_IRN</i> | 0.151 | (0.141) | 0.010 | (0.905) |
| Constant | -0.209* | (0.072) | -0.391*** | (0.000) |
| Observations | 1994 | | 1994 | |
| R^2 | 0.16 | | 0.87 | |
| F | 2.791 | | 93.99 | |

Country and time fixed effects are included for all countries.

*p-values in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

according to our sample the average annual temperature in Syria was 17.42°C in the 1980s, 18.02°C in the 1990s, and 18.6°C in the 2000s. Second, we were interested to investigate a change in temperature growth in our data in order to appreciate the estimation. Similar to the formula above, we took the mean temperature of the 1980s as a reference level, and we computed a mean change in temperature growth for the 16 last available years between 2000 and 2015, comparing to the reference level of 1980s. Thus, we received

$$\frac{\Delta t}{t} = \frac{\bar{t}_{2015-80s} - \bar{t}_{2000-80s}}{\bar{t}_{2000-80s}} = \frac{0.784 - 0.275}{0.275} = \frac{0.509}{0.275} = 1.85, \quad (4)$$

or computed by means of relative temperature change \bar{T} (in %) as

$$\frac{\Delta T}{T} = \frac{\bar{T}_{2015-80s} - \bar{T}_{2000-80s}}{\bar{T}_{2000-80s}} = \frac{3.34 - 1.17}{1.17} = \frac{2.17}{1.17} = 1.85. \quad (5)$$

Surely, we have deviating results because we had a shorter time perspective. Nevertheless, the positive change in temperature of 0.51°C over 16 years is absolutely comparable with an increase of 0.6°C over 20 years, illustrated above. Calculated on average over all countries, we obtained a mean change in temperature growth of 2.17 pp for 16 years (or 0.14 pp annually). Thus, according to our computation, a 2.17 pp increase in temperature growth would induce a reduction in economic growth and food index by 0.67 pp and 0.49 pp, respectively, over 16 years. In other words, only due to rising temperature, every 16 years income growth would fall by 0.67 pp and the food index would decline by 0.49 pp, all else being equal. For example, **if some countries currently have a limited income growth of 1–1.4% annually, in 32 years these countries will be not able to achieve any income growth only due to climate change, ceteris paribus. Additionally, rising food prices due to decreases in harvesting would mean a catastrophe for ordinary citizens in such countries.**

Furthermore, in our estimation neither rainfall level nor its relative change has a significant impact on GDP growth rate or the food index. However, in countries suffering from rain shortages, more precipitation increases economic growth by 0.0002** and the food index by 0.0001*. Furthermore, more water stress decreases the food supply (-0.001***). Considering the third group of political factors, the level of democracy (Polity IV estimates) is significantly negatively related to the food index (-0.008***). In this context, more democratic countries are even less effective in ensuring food production, while stronger autocratic regimes cope better with food supply. Furthermore, democracy level has no significant impact on GDP growth rate. However, the power of political shocks reduces economic growth significantly (-0.007***), regardless of a change in direction of the political system in “transition time”.

Last, with respect to social structure, only increasing ethnic fractionalization reduces the food index (-0.303*). Furthermore, we included some idiosyncratic effects for several cho-

sen Middle Eastern countries. For these four selected countries, the food index appears to have an increasing trend over time compared to 1981. Moreover, it is really interesting that the food index was significantly smaller in Syria than in other countries (-0.518***): this points to the fact that the Syrian government disregarded the importance of agricultural production and provision of food to the population. Next, we are interested to understand how food production shrunk in the years before the Syrian conflict—and to what extent we are able to explain this reduction by reference to temperature growth as the most important explanatory variable for economic indicators.

3.1.1 Predicted impact of temperature growth on economic indicators in Syria

First of all, we would like to point out that the average annual temperature in Syria fluctuates. The mean value of temperature growth rate is 0.316, whereby the interval of the mean \pm standard deviation is [-4.015, 4.647]. In the first column of Table 2, it can be seen that in the years before the war there was a temperature growth rate of 1.932 in 2007 and 8.078 in 2010, whereby the second value lies outside of the computed interval and therefore was an extraordinary change of temperature.

Based on our estimation, we are interested to figure out the extent to which a change in temperature growth can explain the falling income change and food index. Therefore, in columns 2, 4, and 7 we calculated the difference in observed temperature growth, income change rate, and food index when comparing to 2007. The maximum difference in temperature growth rate is 6.147 in 2010, i.e., shortly before the war broke out. Based on our estimates, in columns 5 and 6 we computed partial predicted impact of temperature growth on economic indicators by multiplying the increments with respective coefficients.

Table 2: Predicted effects of temperature growth in Syria

| | $gr_temp, \%$ | Δgr_temp_{y-2007} | gr_gdp_con | Δgr_gdp_{y-2007} | $\hat{\beta}_k \Delta gr_temp_{y-2007}$ | $FI, \%$ | ΔFI_{y-2007} | $\hat{\beta}_m \Delta gr_temp_{y-2007}$ |
|------|----------------|----------------------------|----------------|---------------------------|--|----------|----------------------|--|
| 2007 | 1.932 | | 17.200 | | | 93.600 | | |
| 2008 | 0.235 | -1.697 | 26.085 | 8.885 | 0.526 | 90.040 | -3.560 | 0.385 |
| 2009 | -0.065 | -1.997 | 0.464 | -16.736 | 0.619 | 96.230 | 2.630 | 0.453 |
| 2010 | 8.078 | 6.147 | 10.739 | -6.461 | -1.906 | 91.970 | -1.630 | -1.395 |
| 2011 | -10.543 | -12.475 | 12.096 | -5.104 | 3.867 | 102.840 | 9.240 | 2.832 |
| 2012 | 5.070 | 3.139 | -28.868 | -46.068 | -0.973 | 93.830 | 0.230 | -0.713 |
| 2013 | -2.607 | -4.538 | -40.541 | -57.741 | 1.407 | 83.430 | -10.170 | 1.030 |
| 2014 | 1.929 | -0.003 | -11.730 | -28.930 | 0.001 | 67.790 | -25.810 | 0.001 |
| 2015 | 0.428 | -1.504 | -15.365 | -32.565 | 0.466 | 78.800 | -14.800 | 0.341 |

Thus, shortly before the conflict exploded in 2010, we consider that the 6.15 pp increase in temperature growth contributed to falling income growth by 1.91 pp, whereas the total reduction of income growth was 6.46 pp. In other words, the increase in temperature growth seems to explain around 30% of shrinking income growth. Simultaneously, we observe that the increase in temperature growth by 6.15 pp contributed by decreasing food index by 1.39 pp, where we observe a total reduction of food index of 1.63 pp. This means that based on our estimation, the increase in temperature growth could have

contributed to 85% of the decrease in food index. Surely, we cannot exclude that this result is not shaped by any error term. However, we believe that these findings are reliable. Moreover, based on this empirical evidence, we believe that in the Syrian case, climate change and rapidly rising temperatures essentially contributed to economic instability and food insecurity, which obviously led to rising social tensions and a war. Moreover, we suppose that 2010 was a crucial year generating a considerable deterioration of economic prospects and growing dissatisfaction among the population. To what extent the climate change and economic situation contributed to war, we will reveal in the following.

3.2 Results from the second stage

As explained above, we provide estimation results for the GMM method (Models 1–12 in Table 3) and the IV-2SLS approach (Models 13–24 in Table 4). Each of the two methods was applied for three dependent variables related to conflict. Moreover, to control the stability of the estimation, we included explanatory variables step-by-step in four phases. In this way, we present four models for each independent variable and each method. However, when interpreting results, our discussion will mostly focus only on regressions with the dependent variable “any conflict”, since the impact of explanatory variables on two other dependent variables of conflict is much weaker, and thereby the statistical fit R^2 of respective regressions is lower. However, the results for all dependent variables are very similar, as can be seen from the tables presented. The second-stage equation estimates the impact of economic growth rate and domestic food production (gr_gdp and $food_index$) predicted in the first stage, as well as the impact of other controls X'_{it} added in the regression step-by-step, on the incidence of civil conflict:

$$conflict_dummy_{it} = \alpha_i + \beta \cdot gr_gdp_{it} + \gamma \cdot food_index_{it} + \delta \cdot X'_{it} + \sigma_i \cdot year_t + \epsilon_{it}. \quad (6)$$

As mentioned, we improved our estimations by including climate-relevant, political, and social controls X'_{it} in four phases,⁷ whereas explanatory variables for economic development are included in all steps. Country fixed effect and specific time trend effects are also included in all regressions. In the first phase, we included change in rainfall and temperature. In the second step, we added precipitation level and water availability. Then, we added some additional variables for political system and social structure. Last, we introduced some variables for interaction effects of rain. As can be seen in Table 3, for the GMM method, the results over four described phases are stable when including additional variables step-by-step in Models 1–4 for any conflict and in Models 5–8 for dependent variable *war*, as well as in Models 9–12 for minor conflict. In Table 4, for the

⁷In this paper, we present only significant and stable results controlled by statistical tests for under-identification of instruments, although many other different variables of our database (such as oil exporter status, trade exports, etc.) were regressed on civil conflict. Unfortunately, impacts of other independent variables were insignificant or unstable.

IV-2SLS approach, the addition of further explanatory variables also provides relatively stable results in Models 13–16 for any conflict, in Models 17–20 for *war*, and in Models 21–24 for minor conflict. Since the results are relatively robust over all models, we will mainly focus only on certain specifications.

With respect to the results in model 4, it is very interesting that a 1 pp change in lagged dependent variables increases the probability of any civil conflict significantly by around 0.36 percentage points in the year $(t - 1)$ and by 0.09 pp at time $(t - 2)$. This means that the observed incidence in the past (100% – probability) contributes up to 36% to a conflict likelihood in the future. In this context, there is a strong path-dependency of conflicts over time: a conflict in the past causes a higher probability of an incidence in future.

Furthermore, our estimation establishes a significant negative link between economic development and conflict incidence being robust in all model specifications. Thus, a 1 pp reduction in GDP growth may raise conflict probability by 0.125 pp, while a 1 pp reduction in food production index may increase conflict risk by 0.159 pp. This strong negative link between economic growth and the incidence of civil conflict corresponds with the findings of Miguel et al. (2004). Comparing these outputs with results from Model 16 for the IV-2SLS estimation, we consider an essential overestimation of regression coefficients. For example, a 1 pp reduction in economic variables may induce an increase of conflict risks by 0.391 pp (for GDP growth rate) or even by 0.963 pp (for food index).

Obviously, the IV-2SLS approach considerably overestimates the estimated effects. The reasons for this overestimation of coefficients in the IV-2SLS approach might be that the approach ignores the impact of lagged dependent variables as well as disregarding heteroskedasticity, whereas both may be taken into consideration by the GMM method of Roodman (2009).

However, temperature growth has no significant impact on any conflict; a 1 pp positive change in temperature growth enhances the probability of war by 0.391 pp. Given the average increment in temperature growth of 2.17 pp for the last 16 years in our data, we can calculate that over 32 years, temperature growth can contribute to war probability by 1.7 pp. We think that this effect is a considerable direct contribution of climate change to conflict risks.

Additionally, a 1 pp increase in rainfall growth reduces the likelihood of any civil conflict by around 0.202 pp, and thereby this effect appears to be much stronger for minor conflict than for war (-0.260^{***} versus 0.045). It corresponds to the findings of Miguel et al. (2004), Hendrix and Glaser (2007), and Bohlken and Sergenti (2010) indicating that a positive increase in rainfall growth decreases conflict risk. However, we additionally found that in countries with low levels of precipitation, an increase in rainfall growth enhances the risk of any conflict and minor conflict by 0.196 pp and 0.274 pp, respectively. In this way, the impact of rainfall growth on conflict risk differs between countries in our sample

and among the countries suffering from rain shortage. It appears that in countries with a rain shortage, there might be additional tensions in years with a positive increase in precipitation, as if the countries would fight for rainfall as a water source—if, for example, traditional planting and harvest cycles become disrupted. Another hypothesis is that after extreme weather events, such as strong rainfall and flooding, destruction of natural resources and the usual livelihood conditions may increase the probability of conflict due to higher pressure on agriculture and economies.

Further, regarding annual precipitation level, we observe a positive significant impact of rainfall level on any conflict and minor conflict (0.0003***). This means that the probability of an incidence increases by 0.03 pp when the annual rainfall level changes by 1 mm, or by 3 pp when the rainfall level changes by 100 mm. Our results partly confirm the findings of Ciccone (2011) that higher rainfall level at point $(t - 2)$ is related to the rising risks of conflict at point t . Our results show that a higher rainfall level already at point t is positively related to conflict probability.⁸ However, our results additionally imply that in countries with rainfall shortages, the impact of rainfall level on conflict risk is the reverse. Thus, the likelihood of conflict incidence falls by 0.06 pp when increasing rainfall by 1 mm, or by 6 pp when annual precipitation increases by 100 mm. It appears that a heterogeneity between countries with respect to their crucial level of precipitation may yield different effects on conflict risk. Obviously, in countries with a strong lack of rainfall, the effects of rainfall and rainfall growth do not fit into the entire picture. This phenomenon should be explained more precisely in the future by other variables or more disaggregated data.

Other natural conditions, like available water decreases the probability of any conflict (-0.006***). Thus, the additional possibility of withdrawing 1000 m³ of fresh water per km² reduces the risk of any conflict by 0.06 pp. This also points to the fact that people appear to fight for water sources. However, this stands in contrast to Hendrix and Glaser (2007), who pointed out that freshwater resources per capita are positively associated with the likelihood of conflict.

Regarding the political factors such as level of democracy and government accountability, our results confirm theoretical works indicating that countries with stronger democratic institutions are better able to negotiate compromises among different social groups to avert unrest (Benhabib and Rustichini, 1996; Easterly and Levine, 1997). Thus, the increase in Polity IV scores by one unit implies a significant reduction in the likelihood of any conflict by 0.5 pp. Similarly, the probability of any incidence falls by 0.4 pp when enhancing accountability by one point.

Concerning social structure, in contrast to the results of Miguel et al. (2004) and Fearon and Laitin (2003), who found no significant association of ethnic and religious diversity

⁸We excluded the rainfall levels at time points $(t - 1)$ and $(t - 2)$ because of the test for weak instruments and the high correlation between the different time points.

with civil conflicts, we noted a significantly positive impact of religious fractionalization on conflict risk with the GMM estimator (1.305***). Moreover, the IV-2SLS approach yields a negative impact of ethnic diversity on any conflict and minor conflict (-0.644*** and -0.580***). However, both fractionalizations appear not to be strong predictors for conflict risks because of unstable results dependent upon an estimator and model specification. By contrast, share of urban population seems to provide a stable positive impact on probability of any conflict and minor conflict. Thus, a 1 pp increase in share of urban population enhances the probability of any conflict and minor conflict by 0.7 pp and 1.3 pp, respectively. This indicates that the higher density of the urban population with limited access to job opportunities, food, and fresh water additionally increases the likelihood of being in conflict. That result correlates with findings of other researchers (Nedal et al., 2020; De Soysa, 2002; Raleigh and Urdal, 2007) that highly concentrated states with a greater proportion of urban population are more likely to experience widespread political violence compared to those with a lower share of urban population.

3.2.1 Total predicted effects of conflict probability in Syria

Next, we are interested in computing the extent to which independent variables that were changing in Syria in the years before the conflict are able to explain the likelihood of civil conflict in Syria. Therefore, we take a look at the total effects of probability. We are interested to check how well explanatory variables are able to predict the conflict since 2011 with reference to the previous non-conflict time in Syria. We have taken 2006 as a reference year, i.e., five years before the Syrian civil war broke out. Thus, we compute the total change in predicted probability, $\Delta PROB_{it}$, induced by the increment in the explanatory variable in year t of time period 2007–2015 as:

$$\begin{aligned} \Delta PROB_{it} = & \beta \cdot (gr_gdp_{it} - gr_gdp_{i,2006}) + \gamma \cdot (food_index_{it} - food_index_{i,2006}) + \\ & \delta \cdot (X'_{it} - X'_{i,2006}) + \sigma_i \cdot (year_t - year_{2006}) + (\epsilon_{it} - \epsilon_{i,2006}). \end{aligned} \quad (7)$$

In Table 5, we display the effects. Obviously, some variables (such as *water_1km2*, *ethnic*, *religion*, *urban_pop*) don't contribute to predicted war likelihood because they did not vary over time or they changed only slightly.

Thus, when comparing to 2006, declining economic growth in Syria contributes to a predicted conflict probability only by 0.08 pp in 2011, whereas the maximum of 6.66 pp is reached in 2013. Obviously, this positive effect arises from a negative difference in economic growth rates multiplied by a negative estimated coefficient. When comparing with 2006, falling economic growth is able to explain war likelihood by 3–7 pp. However, in 2009, income growth considerably contributed to conflict risks by 1.5 pp, as well.

Furthermore, the food production index explains the likelihood of conflict only by 0.61 pp in 2011. Overall, the food index is able to predict war probability by 2–6 pp in conflict years and by 1–2 pp in the years before the war. The impact of food index increased over time with increasing intensity of the conflict and reached 6.20 pp in 2014. Interestingly, in the two last years in the dataset, the food index contributes to the conflict likelihood even more strongly than the economic growth (6.2 and 4.44 pp vs. 3.06 and 3.51 pp).

Regarding the total contribution of all rainfall variables (such as *gr_rainfall*, *rainfall*, *inter_L_gr_rainfall*, *inter_L_rainfall*), we computed only minor effects of -1.0, -1.63, 0.25, 0.79, and 0.76 pp after the outbreak of the war. However, in the years before the conflict (2007–2010), low precipitation seems to have sharpened the situation in Syria, because the contribution of all rainfall indicators is mostly positive (such as 1.07, 2.80, -0.68, 1.97 pp). Nevertheless, regarding the years of conflict, both economic variables together are much more able to predict the ongoing conflict (by 7–10 pp) than variables for precipitation.

Furthermore, we recognize an essential effect of temperature growth in the years before the war. All years after 2006 have a positive effect of (respectively) 0.15, 0.04, 0.02, and 0.55 pp in increments of temperature growth when drawing a comparison with 2006. The largest increase in temperature growth was in 2010, shortly before the war began. We suppose that a direct impact of temperature growth on conflict risk (0.55 pp) is a considerable effect when drawing a comparison, for example, with the food index effect of 2.34 pp.

Regarding the official years of conflict, we must admit that it is difficult to explain the Syrian outbreak of war in 2011. Twenty-ten, the year before the conflict erupted, seems to be even more able to explain the conflict likelihood by the selected variables. By contrast, it appears to be possible to explain the ongoing conflict in 2012–2015 by 43–56 pp through involving explanatory variables. However, considering this total effect more closely, it is noticeable that the strongest impact of 36–45 pp arises from lagged dependent variables, whereas the effect of economic variables accounts for 7–10 pp. All other explanatory variables contribute to the conflict relatively weakly.

With the Figure 2.1, we illustrate the contribution of the model components including control variables, lagged conflicts, fixed effects, and errors, to the probability of civil conflict in Syria over time. Numbers from 1 to 35 indicate the time series from 1981 to 2015. It is clear that the model produces high errors in the outbreak years of the early conflict in the '80s and the 2011 conflict. Second, it is obvious from the estimated impact of the controls included in our model, i.e., the impact of the economic, climate variables, political, socio-economic, and demographic, show a trend toward the war that began in 2011 and increased the probability of civil war. (We showed previously that the year 2010 contributed the most to explaining the probability of conflict before the outbreak in 2011.). Third, the impact of controls rises during wartime from 2011 to 2015, indicating

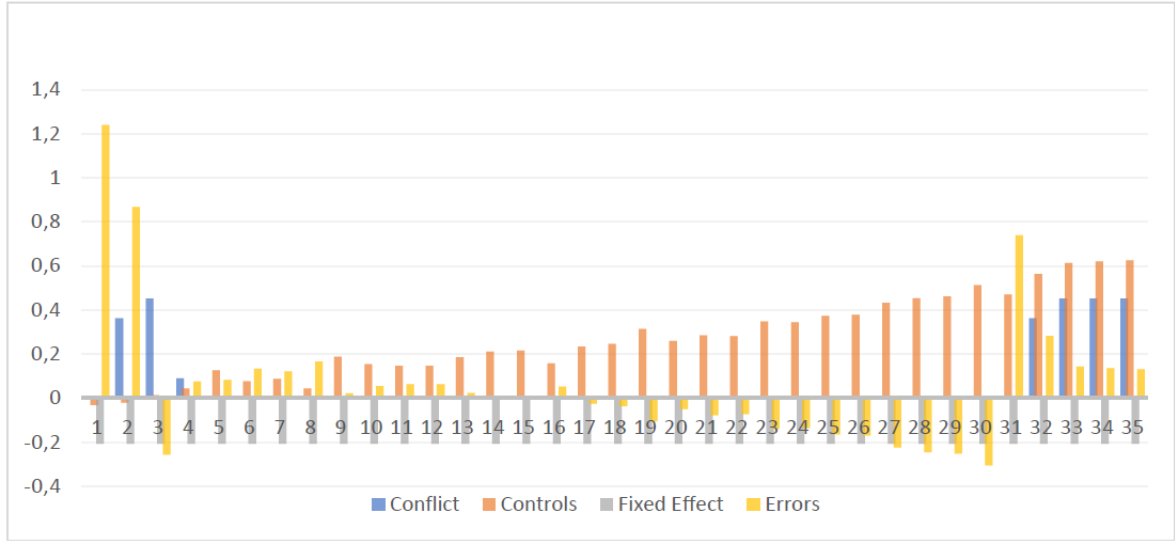


Figure 1: The total contribution of the model components to the probability of civil conflict in Syria from 1981 to 2015

the reverse impact of conflict on the income and food production in the country. Fourth, we see in our model simply that war brings war from the impact of lagged dependent variables (blue bars).

The justification of our work and the criticism of others' studies may be that other researchers don't exactly compute a total contribution of explanatory variables to predicted probability as well as respective residuals. Although some studies investigate marginal effects (estimated coefficients) for the onset of conflict—for example, Fearon and Laitin (2003), Miguel et al. (2004)—they cover neither predicted probabilities nor emerging residuals. Therefore, drawing any conclusions as to the extent to which their significant variables contribute to the onset of conflict is only hardly possible. Apparently, explaining conflict onset is much more difficult than anticipated in our study as well as those of other researchers, and it requires including more country-specific factors. Even significant marginal effects don't guarantee high explanatory power in each specific case.

3.2.2 Political interventions to reduce the incidence of civil conflicts and trigger peace

After presenting empirical evidence on the impacts of climate change on economic development and its contribution to increasing the likelihood of conflict, it is particularly important to assess economic policies that can reverse economic shocks and lead to stable economic development, thus reducing conflict risks. Based on simulation analysis, we anticipate the amount of income growth versus increased food production that can be achieved to country's negative economic growth during war. For example, Syria had in

2012 an economic growth rate of -0.28 pp. Assuming that through global aid it would have been possible to stabilize the economic growth rate of Syria by an amount of money equal to 10% of the Syrian GDP in 2011 (the outbreak-year, i.e., 2011 is a base year "base"). So that, is a certain amount of money or $0,1 * GDP_base$. Using this amount of money as a transfer in the country in year t (which could be 2012, 2013, or 2015) implies the following growth rate:

$$W_GDP = Transfer / GDP_year_{t-1} = 0,1 * GDP_base / (1 - w_year) * GDP_base = 0,1 / (1 - w_year)$$

w_year is the decrease in GDP due to the civil war in the year "year"; Year = 2013, then w_2013 = decline in GDP in 2013 compared to the base year (2011).

For the same amount of money (10% of GDP_base) invested in increasing food production, one needs to know how much production growth can be achieved with a 10% of the base-budget, this is around a 5% food production increase (but permanently, i.e., one-time investment, and the increase occurs each year, like technical progress). The smaller the size of agricultural sector of GDP, the greater this effect. Assuming that the size of the agricultural sector makes up 20% of GDP; $0,5 * 0.2$ / share

Share: is the actual share of the agricultural sector in Syria. While investing in promoting food production also has an impact on GDP, i.e., the indirect growth effect. A 10% of GDP_base investment corresponds to 3% total growth (measured on the GDP_base), therefore, the indirect growth effect increases depending on the size of the actual GDP, so this multiplied by $1 / (1 - w_year)$ gives the actual effect.

Figure 2 shows the simulation results of the relative effects of political interventions (Transfer compared to food policy) in stabilizing economic development, thus reducing the incidence of civil conflict, and triggering peace. The orange bars indicating policy interventions that accelerate economic growth rate show a higher effect in the first year than the effect of food policy (green bars) and this effect remains the same in the following years, while policies that enhance food production (technical progress) indicate a higher effect in the following years due to the effect of the previous year (cumulative).

Therefore, proper food policies that enhance food security seem to play a more affordable role towards peace. Accordingly, policy intervention that are able to increase food security as well as global aid to accelerate economic development, have the potential to reduce the risk of conflict and triggering peace. The findings of this study are relevant to other countries in the region that face comparable environmental challenges and can inform policies for mitigating and alleviating future conflicts.

It is especially important to assess economic policies that can lead to stable economic development, and thus reduce the risks of political conflicts. In doing so, based on simulation analysis, we anticipate how much income growth can be achieved by stabilizing a country's negative economic growth during wartime. For example, Syria had in 2012 an economic growth rate of -0.24 pp, assuming that through global aid it would have been

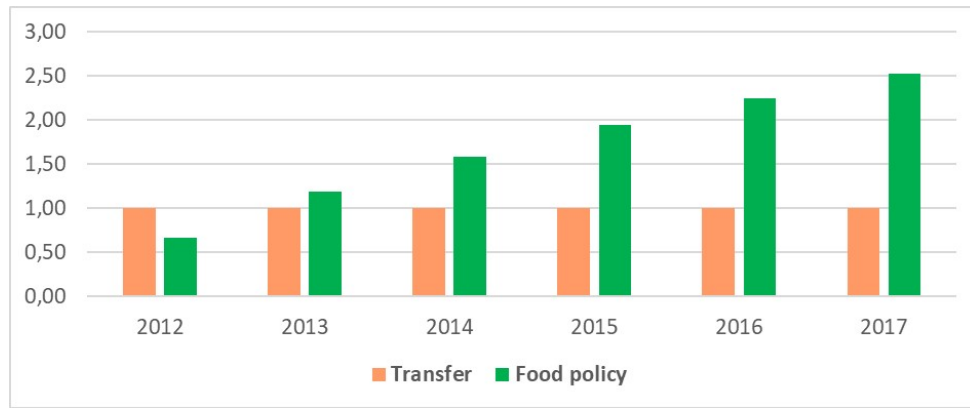


Figure 2: Relative effects of policy interventions triggering peace

possible to stabilize the economic growth rate of Syria by an amount of money equal to 5% of the Syrian GDP in 2012, then this would lead to an increase of the economic growth rate of 2012 by 0.04 pp. For the same amount of money (5% of GDP in 2012) invested in increased in food production it would add 0.07 pp on food production in 2012. Therefore, proper food policies that enhance food security seem to play a role toward peace.

However, when war breaks out, it leads to a greater decline in the economic growth rate, that is, it is no longer related to the negative effects of climate on the economic growth. To achieve the same amount of income growth during a war, a greater amount of money would be needed compared to a pre-war situation. For example, to achieve an additional 0.03 pp economic growth rate in 2014 when the war intensified, it would need an amount of money equal to 12% of Syrian GDP in 2012. These results indicate the importance of taking appropriate measures, especially at the outbreak of war, otherwise the costs of returning back to peace are increasing over time.

4 Conclusion

This paper evaluates the linkages between climate change, economic indicators, and conflict probability based on a new panel database. This data sample includes many socio-economic, political, and environmental variables for 59 countries of Africa and the Middle East from 1981 to 2015, collected from different prominent resources. While many studies try to explain conflict probability using only data of the African continent, we believe that it is important to also take into account countries of the Middle East suffering from social tensions related to climate change. We contributed to current research in the following ways.

First, we investigated an indirect impact of climate change on war probability through its effect on economic development. In addition to other environmental and socio-political characteristics, weather indicators seem to be suitable instrumental variables not only for economic growth but also for domestic food production index. For example, a 1 pp change in temperature growth can significantly decrease income growth (by 0.31 pp) and food index (by 0.23 pp), respectively. This is a huge effect. For example, while in the 2000s the global mean temperature difference was around 0.6°C above pre-industrial levels (1850–1900), in 2019 this temperature change was already around $1.1 \pm 0.1^{\circ}\text{C}$ (World Meteorological Organization, 2019): that means a near doubling of temperature growth, or a 100% increase during only 20 years. Regarding countries in our dataset, we found a 185% increase of temperature growth during the last 16 years of the sample when comparing with the '80s. We calculated a mean change in temperature growth of 2.17 pp during the last 16 years. By means of estimated coefficients, it can be seen that a reduction in economic growth is 0.67 pp during 16 years, whereas reduction in food index is 0.49 pp. This means that **if some countries currently have an income growth rate of 1–1.4% annually, within only 32 years these countries will be not able to achieve any income growth only due to climate change, ceteris paribus.**

Second, we found that climate change directly affects the likelihood of civil war. According to our estimation, a 1 pp change in temperature growth can cause an increase in war probability of 0.391 pp. Taking the average increment in temperature growth of 2.17 pp for the 16 years, we calculated that for 32 years, temperature growth alone can contribute to war probability by 1.7 pp. With other factors, that may be crucial for a war breaking out. Regarding the impact of precipitation on conflict likelihood, our findings imply that a 1 pp increase in rainfall growth reduces the mean likelihood of any civil conflict by 0.2 pp. However, in countries with high rainfall shortage, the result is the opposite, i.e., an increase in rainfall growth enhances any conflict risk by around 0.2 pp. Overall, our results indicate that the effect of both rainfall variables on conflict likelihood may be significantly different according to countries' dependence on usual precipitation level.

Third, we confirmed the most robust finding of Miguel et al. (2004): that economic situations induced by climate variability can significantly raise the risk of conflict. Additionally to GDP growth, the food production index appears to be a further appropriate economic variable for explaining conflict probability. Considering all countries, a 10% reduction in economic growth or domestic food production leads to 1,2% and 1,59% increase in the probability of civil conflict, respectively. In this context, economic development must play an essential role for preventing any conflicts.

Fourth, ignoring lagged dependent variables leads to overestimation of marginal effects. Our results, based on comparing two different approaches, point to the fact that other studies usually overestimate the impact of economic and weather variables on conflict probability because effects of lagged dependent variable were not taken into account. According to our results, being in conflict in the past enhances a likelihood of further incidence by 36–45 pp and automatically decreases the significant effects of other explanatory variables. The simple logic behind our motivation for involving lagged dependent variable is that human losses cause psychological obstacles and barriers to peace-building.

Next, our results show that increases in temperature growth have a great impact on a country's economic situation. For Syria, based on our estimation, we found out that the strong increase in temperature growth explains 30% of shrinking income growth as well as 85% of decreasing food index in 2010. Moreover, we suppose that 2010 was a crucial year generating a high probability for war. The high increase in temperature growth in 2010 strongly contributed to economic instability and food insecurity, and (as can be seen in the next step), both obviously led to rising social tensions.

Thus, we explained the Syrian conflict by our estimates. The effects over explanatory variables in 2010 point to the rising probability of conflict. While the onset of the conflict in 2011 could not be explained well, the ongoing conflict in 2012–2015 could be empirically predicted by explanatory variables to the tune of 43–56%. Obviously, the strongest factor explaining the ongoing conflict is the occurrence of war in the last two years: it accounts for up to 45% of conflict likelihood. The second important factor contributing to conflict risks arises from both economic variables. We empirically showed that an unstable economic situation, decreasing income, and food insecurity essentially contributed to the Syrian conflict. Thus, GDP change and food index together seem to have contributed to conflict in Syria by 7–10%. Moreover, both economic variables are much more able to predict the ongoing conflict than variables for climate change.

Moreover, we would like to point to the fact that obtaining a significant impact of explanatory variables on dependent conflict variables is easier than receiving a highly predicted probability itself. The investigation of causes of conflict requires much more than only receiving significant coefficients. To understand each current incidence and empirical estimation, it is much more interesting and helpful to reveal total effects and predicted probabilities. Explaining each current incidence requires the inclusion of more country-

specific factors. Notice that while growth indicators calculated as year-by-year change give researchers only a short perspective for analysis, serious consequences of climate change are much more noticeable by considering a long-term perspective. Therefore, for empirical investigation, it is recommended to calculate indicators of temperature growth and rainfall growth based on a period of time longer than one year. Last, the investigation of the onset of conflict requires more precise attention in the future. Proper economic policies that stabilize the negative GDP growth and enhance food production index play a role in reducing the risk of civil conflict.

Table 3: Estimation results of dynamic GMM method with lagged dependent variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|---------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | any_prio | any_prio | any_prio | any_prio | war_prio | war_prio | war_prio | war_prio | minor_prio | minor_prio | minor_prio | minor_prio |
| <i>L.amg_prio</i> | 0.377*** (0.000) | 0.374*** (0.000) | 0.366*** (0.000) | 0.361*** (0.000) | 0.313*** (0.000) | 0.311*** (0.000) | 0.308*** (0.000) | 0.308*** (0.000) | 0.272*** (0.000) | 0.271*** (0.000) | 0.266*** (0.000) | 0.262*** (0.000) |
| <i>L2.any_prio</i> | 0.100** (0.030) | 0.096** (0.041) | 0.089* (0.062) | 0.090* (0.057) | 0.111** (0.010) | 0.111** (0.012) | 0.109** (0.015) | 0.108** (0.015) | 0.069* (0.071) | 0.067* (0.081) | 0.062 (0.110) | 0.061 (0.115) |
| <i>L2.var_prio</i> | | | | | | | | | -0.064 (0.242) | -0.063 (0.258) | -0.060 (0.279) | -0.050 (0.366) |
| <i>L2.minor_prio</i> | | | | | | | | | -0.120* (0.069) | -0.103 (0.129) | -0.120* (0.069) | -0.112* (0.078) |
| <i>gr.gdp_c_con</i> | -0.132** (0.037) | -0.133** (0.038) | -0.133** (0.037) | -0.125** (0.047) | -0.084** (0.022) | -0.086** (0.022) | -0.087** (0.017) | -0.088** (0.016) | -0.081** (0.052) | -0.063 (0.258) | -0.060 (0.279) | -0.050 (0.366) |
| <i>food_index</i> | -0.130** (0.030) | -0.140** (0.016) | -0.166*** (0.003) | -0.159*** (0.003) | -0.067* (0.088) | -0.073* (0.073) | -0.081* (0.052) | -0.081** (0.050) | -0.064 (0.242) | -0.063 (0.258) | -0.060 (0.279) | -0.050 (0.366) |
| <i>gr.temp</i> | 0.035 (0.880) | 0.124 (0.596) | 0.113 (0.633) | 0.066 (0.777) | 0.319 (0.106) | 0.383** (0.047) | 0.380** (0.048) | 0.391** (0.046) | -0.099 (0.150) | -0.103 (0.129) | -0.120* (0.069) | -0.112* (0.078) |
| <i>gr.minor_prio</i> | -0.024* (0.052) | -0.037*** (0.005) | -0.036*** (0.006) | -0.202*** (0.007) | -0.001 (0.953) | -0.012 (0.188) | -0.011 (0.218) | 0.045 (0.392) | -0.260 (0.455) | -0.223 (0.515) | -0.233 (0.498) | -0.298 (0.373) |
| <i>rainfall</i> | | 0.0001 (0.124) | 0.0001 (0.176) | 0.0003*** (0.002) | -0.001 (0.953) | 0.0001* (0.048) | 0.0001* (0.058) | 0.0001 (0.424) | -0.020 (0.136) | -0.022 (0.135) | -0.025 (0.144) | -0.260*** (0.003) |
| <i>water.lkm2</i> | | -0.005*** (0.003) | -0.006*** (0.004) | -0.006*** (0.006) | | -0.002 (0.472) | -0.0025 (0.465) | -0.002 (0.461) | | 0.00002 (0.810) | 0.00001 (0.945) | 0.0003*** (0.020) |
| <i>polityiv.tr</i> | | -0.005* (0.051) | -0.005* (0.051) | -0.005* (0.051) | | -0.003 (0.149) | -0.003 (0.149) | -0.003 (0.134) | | -0.004* (0.082) | -0.002 (0.356) | -0.004* (0.089) |
| <i>accountab</i> | | -0.004** (0.024) | -0.004** (0.022) | -0.004** (0.022) | | -0.002** (0.045) | -0.002** (0.045) | -0.002** (0.045) | | -0.002 (0.366) | -0.003* (0.061) | -0.003* (0.061) |
| <i>ethnic</i> | | -0.379 (0.082) | -0.379 (0.280) | -0.379 (0.280) | | 0.307 (0.236) | 0.307 (0.236) | 0.280 (0.283) | | -0.445 (0.501) | -0.445 (0.501) | -0.445 (0.501) |
| <i>urban.pop</i> | | 1.116** (0.046) | 1.116** (0.046) | 1.305*** (0.008) | | 0.765 (0.142) | 0.765 (0.142) | 0.765 (0.142) | | 0.297 (0.662) | 0.297 (0.662) | 0.297 (0.662) |
| <i>inter.L_gr_rainfall</i> | | 0.008 (0.130) | 0.008 (0.130) | 0.007 (0.161) | | -0.003 (0.479) | -0.003 (0.479) | -0.003 (0.479) | | 0.014** (0.019) | 0.014** (0.019) | 0.014** (0.019) |
| <i>inter.L_minfall</i> | | 0.196*** (0.010) | 0.196*** (0.010) | 0.196*** (0.010) | | -0.057 (0.251) | -0.057 (0.251) | -0.057 (0.251) | | | | 0.274*** (0.002) |
| <i>year.trend_TUR</i> | -0.001 (0.643) | 0.002 (0.313) | -0.003 (0.452) | -0.002 (0.612) | -0.004*** (0.000) | -0.003*** (0.026) | -0.001 (0.672) | -0.001 (0.645) | 0.005*** (0.001) | 0.007*** (0.000) | -0.002 (0.706) | -0.001*** (0.007) |
| <i>year.trend_SYR</i> | 0.020*** (0.000) | 0.019*** (0.000) | 0.018*** (0.000) | 0.018*** (0.000) | 0.012*** (0.000) | 0.012*** (0.000) | 0.013*** (0.000) | 0.013*** (0.000) | 0.010*** (0.000) | 0.010*** (0.000) | 0.007*** (0.000) | 0.006*** (0.000) |
| <i>year.trend_IRQ</i> | 0.005*** (0.000) | 0.009*** (0.000) | 0.012*** (0.000) | 0.011*** (0.000) | 0.019*** (0.000) | 0.021*** (0.000) | 0.022*** (0.000) | 0.023*** (0.000) | -0.017*** (0.000) | -0.014*** (0.000) | -0.012*** (0.000) | -0.013*** (0.000) |
| <i>dummy_country_TUR</i> | 0.004** (0.019) | 0.005*** (0.003) | -0.001 (0.820) | -0.001 (0.788) | 0.005*** (0.000) | 0.005*** (0.000) | 0.007** (0.014) | 0.007** (0.015) | 0.001 (0.740) | 0.001 (0.521) | -0.008** (0.040) | -0.008** (0.030) |
| <i>dummy_country_SYR</i> | -0.066 (0.187) | 0.706*** (0.000) | 1.109*** (0.000) | 1.175*** (0.000) | -0.331*** (0.000) | 0.433*** (0.005) | 0.476*** (0.000) | 0.482*** (0.002) | 0.395*** (0.000) | -0.472 (0.339) | -0.008** (0.040) | 0.852*** (0.000) |
| <i>dummy_country_IRQ</i> | -0.918*** (0.000) | 0.098 (0.636) | -0.077 (0.677) | -0.244 (0.195) | -0.741*** (0.000) | -0.433*** (0.000) | -0.072 (0.598) | -0.330*** (0.000) | -0.154*** (0.000) | -0.819** (0.032) | -0.191 (0.354) | 0.110 (0.574) |
| <i>dummy_country_IRN</i> | -0.279*** (0.000) | 0.861*** (0.001) | 0.408** (0.028) | 0.270*** (0.010) | -0.678*** (0.000) | 0.241 (0.407) | 0.144 (0.676) | -0.160* (0.092) | 0.577*** (0.000) | -0.033 (0.927) | 0.376* (0.068) | 0.528*** (0.000) |
| <i>dummy_country_IRN</i> | -0.409*** (0.000) | 0.457*** (0.009) | 0.698** (0.037) | 0.539*** (0.000) | -0.649*** (0.000) | 0.167 (0.352) | -0.00627 (0.970) | -0.053 (0.722) | 0.336*** (0.000) | -0.477 (0.313) | 0.221 (0.568) | 0.721*** (0.000) |
| Constant | 0.714*** (0.000) | 0.105 (0.534) | -0.272** (0.037) | -0.211 (0.113) | 0.595*** (0.000) | -0.142 (0.220) | 0.007 (0.933) | 0.002 (0.981) | 0.091 (0.134) | 1.111* (0.063) | -0.395*** (0.004) | -0.327** (0.018) |
| Observations | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 | 1871 |

Table 4: Estimation results of dynamic IV-2SLS method

| | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) |
|----------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| | any_prio | any_prio | any_prio | any_prio | any_prio | war_prio | war_prio | war_prio | minor_prio | minor_prio | minor_prio | minor_prio |
| <i>gr.gdp_c_con</i> | -0.487*** (0.003) | -0.492*** (0.001) | -0.449*** (0.004) | -0.391** (0.011) | -0.246*** (0.008) | -0.257*** (0.005) | -0.239*** (0.006) | -0.251*** (0.006) | -0.255** (0.045) | -0.250*** (0.043) | -0.222* (0.090) | -0.151 (0.263) |
| <i>food_index</i> | -0.604** (0.040) | -0.703** (0.013) | -0.975*** (0.000) | -0.963*** (0.000) | 0.019 (0.907) | -0.027 (0.877) | -0.084 (0.722) | -0.090 (0.710) | -0.607* (0.066) | -0.660** (0.038) | -0.872*** (0.002) | -0.853*** (0.003) |
| <i>gr.temp</i> | -0.206 (0.337) | -0.074 (0.740) | -0.121 (0.615) | -0.150 (0.533) | 0.169 (0.520) | 0.225 (0.367) | 0.223 (0.384) | 0.226 (0.381) | -0.363 (0.225) | -0.257 (0.332) | -0.331 (0.262) | -0.364 (0.205) |
| <i>gr.minor_prio</i> | -0.022** (0.024) | -0.044*** (0.000) | -0.044*** (0.001) | -0.274*** (0.001) | -0.005 (0.551) | -0.016** (0.034) | -0.015** (0.039) | 0.016 (0.721) | -0.018* (0.089) | -0.029** (0.025) | -0.030** (0.024) | -0.297*** (0.002) |
| <i>rainfall</i> | | 0.0002* (0.011) | 0.0002* (0.017) | 0.0004*** (0.000) | -0.005 (0.907) | 0.0001** (0.043) | 0.0001* (0.052) | 0.001 (0.348) | | 0.0001 (0.205) | 0.0001 (0.218) | 0.0004*** (0.004) |
| <i>water.lkm2</i> | | -0.008*** (0.001) | -0.009*** (0.000) | -0.009*** (0.000) | -0.009*** (0.000) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.005 (0.160) | -0.006 (0.105) | -0.006 (0.102) |
| <i>polityiv.tr</i> | | -0.008*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.007 (0.197) | -0.007 (0.197) | -0.004** (0.043) |
| <i>ethnic</i> | | -0.008*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.004** (0.043) | -0.004** (0.043) | -0.004** (0.043) |
| <i>urban.pop</i> | | -0.008*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.007 (0.197) | -0.007 (0.197) | -0.004** (0.043) |
| <i>inter.L_gr_rainfall</i> | | -0.008*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.007 (0.197) | -0.007 (0.197) | -0.004** (0.043) |
| <i>inter.L_minfall</i> | | -0.008*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.009*** (0.001) | -0.003 (0.490) | -0.003 (0.490) | -0.003 (0.490) | | -0.007 (0.197) | -0.007 (0.197) | -0.004** (0.043) |
| <i>year.trend_TUR</i> | 0.020*** (0.000) | 0.026*** (0.000) | 0.017** (0.074) | 0.018** (0.065) | -0.004 (0.179) | -0.002 (0.576) | -0.001 (0.931) | -0.001 (0.931) | 0.024*** (0.000) | 0.028*** (0.000) | 0.017*** (0.040) | 0.017*** (0.033) |
| <i>year.trend_SYR</i> | 0.021*** (0.000) | 0.022*** (0.000) | 0.022*** (0.000) | 0.022*** (0.000) | 0.004 (0.122) | 0.005 (0.111) | 0.006 (0.156) | 0.006 (0.163) | 0.017*** (0.002) | 0.017*** (0.001) | 0.016*** (0.002) | 0.015*** (0.003) |
| <i>year.trend_IRQ</i> | 0.006*** (0.000) | 0.013*** (0.000) | 0.013*** (0.000) | 0.013*** (0.000) | 0.030*** (0.000) | 0.032*** (0.000) | 0.034*** (0.000) | 0.034*** (0.000) | -0.024*** (0.000) | -0.019*** (0.000) | -0.016*** (0.001) | -0.017*** (0.000) |
| <i>year.trend_IRN</i> | 0.013 (0.141) | 0.016* (0.064) | 0.017 (0.191) | 0.015 (0.239) | -0.0002 (0.974) | 0.001 (0.864) | 0.004 (0.662) | 0.004 (0.640) | 0.013 (0.201) | 0.015 (0.141) | 0.011 (0.312) | 0.009 (0.408) |
| <i>dummy_country_TUR</i> | 0.718*** (0.000) | 1.024*** (0.000) | 0.556 (0.513) | 2.018* (0.062) | 0.291*** (0.000) | 0.433*** (0.000) | 1.005 (0.169) | 0.709 (0.429) | 0.429*** (0.000) | 0.595*** (0.000) | -0.439 (0.601) | 1.363 (0.214) |
| <i>dummy_country_SYR</i> | -0.132* (0.066) | 0.550*** (0.001) | -0.349 (0.340) | 0.132 (0.717) | 0.019 (0.028) | 0.297 (0.229) | 0.238 (0.143) | 0.143 (0.633) | -0.146* (0.068) | 0.256 (0.240) | -0.013** (0.043) | -0.022 (0.951) |
| <i>dummy_country_IRQ</i> | 0.898*** (0.000) | 1.798*** (0.000) | 0.565 (0.317) | 0.838 (0.115) | -0.201*** (0.000) | 0.161 (0.622) | 0.049 (0.908) | -0.001 (0.997) | 1.095*** (0.000) | 1.630*** (0.000) | 0.454 (0.346) | 0.786* (0.066) |
| <i>dummy_country_IRN</i> | 0.448*** (0.000) | 0.893*** (0.000) | 0.104 (0.880) | 1.394 (0.101) | 0.240*** (0.000) | 0.436** (0.001) | 0.801 (0.151) | 0.547 (0.446) | 0.214* (0.055) | 0.463*** (0.004) | -0.699 (0.308) | 0.884 (0.323) |
| Constant | 0.380** (0.047) | 0.343* (0.092) | 0.561 (0.405) | -0.656 (0.485) | -0.021 (0.840) | -0.082 (0.610) | -0.388 (0.659) | -0.147 (0.883) | 0.390* (0.069) | 0.410 (0.137) | 0.882 (0.336) | -0.612 (0.580) |
| Observations | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 | 1994 |
| <i>R²</i> | 0.55 | 0.54 | 0.53 | 0.54 | 0.38 | 0.39 | 0.39 | 0.39 | 0.43 | 0.43 | 0.41 | 0.42 |
| <i>F</i> | 0.107 | 0.253 | 0.798 | 1.071 | 0.0805 | 0.203 | 0.117 | 0.302 | 0.0662 | 0.131 | 0.713 | 0.628 |

Fixed effects and specific time trends are included for all countries

p-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Total effects of explanatory variables, compared to 2006

| | <i>any_prio_lag_1</i> | <i>any_prio_lag_2</i> | <i>gr_gdp_c_con</i> | <i>food_index</i> | <i>gr_temp</i> | <i>gr_rainfall</i> | <i>rainfall</i> | <i>water_1km2</i> | <i>polityiv_tr</i> | <i>accountab</i> | <i>ethnic</i> | <i>religion</i> | <i>urban_pop</i> | <i>inter_L_gr_rainfall</i> | <i>inter_L_rainfall</i> | Sum over vars. | Constants | Residuals |
|------|-----------------------|-----------------------|---------------------|-------------------|----------------|--------------------|-----------------|-------------------|--------------------|------------------|---------------|-----------------|------------------|----------------------------|-------------------------|----------------|-----------|-----------|
| 2007 | 0.00 | 0.00 | -0.55 | 2.08 | 0.15 | 4.39 | -1.10 | 0.00 | 0.00 | 0.18 | 0.00 | 0.00 | 0.72 | -4.26 | 2.03 | 3.64 | -19.35 | 15.72 |
| 2008 | 0.00 | 0.00 | -1.66 | 2.65 | 0.04 | 7.13 | -3.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.72 | -6.92 | 5.62 | 4.54 | -17.57 | 13.03 |
| 2009 | 0.00 | 0.00 | 1.54 | 1.66 | 0.02 | -11.31 | 0.40 | 0.00 | 0.00 | -0.32 | 0.00 | 0.00 | 0.72 | 10.98 | -0.75 | 2.93 | -15.78 | 12.85 |
| 2010 | 0.00 | 0.00 | 0.25 | 2.34 | 0.55 | 7.39 | -2.04 | 0.00 | 0.00 | 0.03 | 0.00 | 0.00 | 1.43 | -7.17 | 3.79 | 6.57 | -14.00 | 7.43 |
| 2011 | 0.00 | 0.00 | 0.08 | 0.61 | -0.67 | -7.70 | 0.90 | 0.00 | 0.00 | 0.38 | 0.00 | 0.00 | 0.72 | 7.47 | -1.66 | 0.13 | -12.21 | 112.08 |
| 2012 | 36.12 | 0.00 | 5.20 | 2.05 | 0.36 | -0.44 | 1.90 | 0.00 | 0.93 | 0.56 | 0.00 | 0.00 | 0.00 | 0.43 | -3.51 | 43.58 | -10.43 | 66.84 |
| 2013 | 36.12 | 9.05 | 6.66 | 3.71 | -0.15 | 5.67 | -0.10 | 0.00 | 0.93 | 0.56 | 0.00 | 0.00 | -0.72 | -5.50 | 0.18 | 56.42 | -8.64 | 52.23 |
| 2014 | 36.12 | 9.05 | 3.06 | 6.20 | 0.15 | 3.48 | -0.81 | 0.00 | 0.93 | 0.50 | 0.00 | 0.00 | -1.43 | -3.38 | 1.50 | 55.38 | -6.86 | 51.48 |
| 2015 | 36.12 | 9.05 | 3.51 | 4.44 | 0.05 | 1.81 | -0.83 | 0.00 | 0.93 | 0.68 | 0.00 | 0.00 | -1.43 | -1.75 | 1.54 | 54.13 | -5.07 | 50.94 |

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Appendix A

Data set and variable description

Preface

In order to estimate the impact of climate and induced economic shocks, social fragmentation, and political status on the incidence of civil conflict in country i year t , we use new cross-section panel data collected from various recognized sources providing consistently updated time series, for African and Middle East countries (total 59) from 1981 to 2015. We relied only on one source to cover all observations for one variable. However, some variables, especially those related to development indicators, suffer from missing for some cross-sections, but however, in the end, we choose the source that contains fewer missing and we use a technique that deals with missing values (replaced missing values by the mean value of each variable in each country).

We make this data set available in STATA format, which consists of the following data and variables:

Identification variables

- country_code

The three letter codes (ISO alpha-3) are internationally recognized codes that designate every country, from United Nation ISO 3166-1 alpha-3 ⁹.

- country_name

Country name: Almost all Sub-Saharan Africa countries are the same as in the study of Miguel et al. (2004)¹⁰.

⁹Total sample observations are 2029, Namibia starts from 1990 after independence.

¹⁰Note: MSS indicated that Eritrea and Equatorial Guinea were dropped from the analysis due to lack of data, and For Djibouti, Liberia, and Somalia, GDP data are missing since 1992. For Sudan and the Democratic Republic of Congo, GDP data are missing for 1999. Namibia became independent in 1990. Although the sources of our data provides a complete time series but we present and include same number of observations as by MSS in the estimations, to be comparable.

- ccode

The numeric country codes; for countries that match the MSS-sample, we keep the same codes, for the rest countries of our sample, three numeric codes were also randomly assigned. This variable is used only to facilitate data binding, not more.

- year

From 1981 to 2015. Only Namibia starts in 1990, after independence.

Civil conflict data and derivation of variables

We use for conflict variables the UCDP/PRIO Armed Conflict Dataset, a conflict version 18.1. ((Themnér et al., 2018)), developed by the Uppsala Conflict Data Program (UCDP) at the Department of Peace and Conflict Research, Uppsala University in Sweden and the International Peace Research Institute in Oslo (PRIO)¹¹

An armed conflict is defined by the PRIO/Uppsala as a contested incompatibility that concerns government and/or territory over which the use of armed force between two parties, of which at least one is the government of a state, has resulted in at least 25 battle-related deaths in one calendar year.

We focus on civil wars, in the PRIO/Uppsala conflict data four types of conflict are classified (type 1, 2, 3, and 4), type3 and type4 cover civil conflicts without and with intervention from other states on one or both sides ¹², respectively.

The values that each of type3 and type4 of a civil conflict can take are as follows:

TYPE3:

This type of conflict is the PRIO/Uppsala's indicator of Internal Conflict. It can take on four distinct values: 0: No Internal Conflict, 1: Internal Minor Armed Conflict, 2: Internal Intermediate Armed Conflict, 3: Internal War.

TYPE4:

Whereas this type of conflict is the PRIO/Uppsala's indicator of Internationalized Internal Conflict. It can take on four distinct values: 0: No Internationalized Internal Conflict, 1:Internationalized Internal Minor Armed Conflict, 2:Internationalized Internal Intermediate Armed Conflict, 3:Internationalized Internal War¹³.

While the intensity level of a conflict in a given year distinguishes minor armed conflicts from wars based on the battle-related deaths¹⁴ :

¹¹The UCDP/PRIO armed conflict for download <http://ucdp.uu.se/downloads/>.

¹²Side A, is always the government side in intrastate conflicts; side B, is the country or opposition organization(s) (The PRIO/Uppsala conflict data, 18.1. 2017).

¹³This is very well documented in the mss_manual as well, p.16 (MSS data set, 2004), the source is the PRIO/Uppsala conflict data.

¹⁴UCDP/PRIO Armed Conflict Dataset Codebook, version 4_2009, updated by: Harbom et al. (2009). The dataset was first presented in Gleditsch et al. (2002), and is available for download from:

1. Minor: between 25 and 999 battle-related deaths in a given year.
2. War: at least 1,000 battle-related deaths in a given year.

Conflict variables and derived

We construct three dependent conflict variables (any conflict, minor, and war), all country-year observations are coded as ones based on the type (3 and 4) and the intensity level of the PRIO/Uppsala conflict data as follows:

1. **war_prio**: War equals 1 when the type of conflict in year t is 3 or 4 and has an intensity level of 2 (at least 1,000 battle-related deaths per year).
war_prio_lag_1: Lagged one year.
war_prio_lag_2: Lagged two years.
2. **minor_prio**: Minor conflict equals 1 when the type of conflict in year t is 3 or 4 and has an intensity level of 1 (at least 25 battle-related deaths per year and fewer than 1,000 battle-related deaths during the course of the conflict).
minor_prio_lag_1: Minor conflict lagged one year.
minor_prio_lag_2: Minor conflict lagged two years.
3. **any_prio**: Any conflict equals 1 when minor conflict or war equals 1. Otherwise, are coded as zeros.
any_prio_lag_1: Any conflict lagged one year.
any_prio_lag_2: Any conflict lagged two years.

Weather variables

We employ two rainfall data sets:

1. **The historical climate data provided at** World Bank Climate Change Knowledge Portal (2018).

We observe changes in rainfall variable from the previous year following (Miguel et al., 2004): $\text{gr_rainfall} = \frac{\text{rainfall} - \text{rainfall_lag1}}{\text{rainfall_lag1}}$

For the climate (precipitation) measurement strategy in this thesis, we have included and generated the following variables:

Rainfall variables and derived

- **rainfall**: The annual rainfall (millimeter) is computed by adding up all of the monthly observations in a given year.
- **rainfall_lag_1**: Lagged one year.

- **rainfall_lag_2:** Lagged two years.
- **gr_rainfall:** Growth in rainfall: $(\text{rainfall} - \text{rainfall_lag1})/(\text{rainfall_lag1})$.
- **gr_rainfall_lag_1:** Growth rainfall lagged one year:
 $(\text{rainfall_lag_1} - \text{rainfall_lag_2})/(\text{rainfall_lag_2})$.
- **log_rainfall:** Log of rainfall levels.
- **log_rainfall_lag_1:** Lagged one year.
- **log_rainfall_lag_2:** Lagged two years.

In order to examine some interaction effects (rainfall) following variables have been generated:

- **dummy__gr_rain_neg:** Equals 1 if a change in rainfall variable in country i year t from the previous year is less than zero (1 if $\text{gr_rainfall} < 0$), otherwise zeros.
- **dummy__gr_rain_pos:** Equals 1 if a change in rainfall variable in country i year t from the previous year is greater than zero (1 if $\text{gr_rainfall} > 0$), otherwise zeros.
- **dummy__rain_pos:** Equals 1 if rainfall level in country i year t is greater than the mean of rainfall level variable of the sample (1 if $\text{rainfall} > 57.98657$).
- **dummy__rain_neg:** Equals 1 if the value of rainfall level in country i year t is less than the mean of rainfall levels in the sample (1 if $\text{rainfall} < 57.98657$).
- **inter_pos_pos:** Interaction effect between measures of positive growth rainfall and positive rainfall levels; $(\text{dummy_gr_rain_pos} * \text{dummy_rain_pos})$.
- **inter_pos_neg:** Interaction effect between measures of positive growth rainfall and negative rainfall levels; $(\text{dummy_gr_rain_pos} * \text{dummy_rain_neg})$.
- **inter_neg_pos:** Interaction effect between measures of negative growth rainfall and positive rainfall levels; $(\text{dummy_gr_rain_neg} * \text{dummy_rain_pos})$.
- **inter_neg_neg:** Interaction effect between measures of negative growth rainfall and negative rainfall levels; $(\text{dummy_gr_rain_neg} * \text{dummy_rain_neg})$.

Moreover, several variables are generated to consider the effect of precipitation depending on where it falls, and thus, we determined whether our sample countries had historically low or high precipitation rates compared to the average precipitation in Europe. (Germany took specifically: 727 mm) to build interaction effects as follows.

- **low_rainfall_countr:** Dichotomous variable equals 1 if the annual rainfall levels of a country is lower than 727 mm, otherwise zero.
- **high_rainfall_countr:** Dichotomous variable equals 1 if the annual rainfall levels of a country is higher than 727 mm, otherwise zero.
- **inter_L_gr_rainfall:** Interaction effect between the dummy variable "low_rainfall_countr" and measures of rainfall growth "gr_rainfall" in country (*i*) time (*t*).
- **inter_h_gr_rainfall:** Interaction effect between the dummy variable "high_rainfall_countr" and measures of rainfall growth "gr_rainfall" in country (*i*) time (*t*).
- **inter_l_rainfall:** Interaction effect between the dummy variable "low_rainfall_countr" and measures of rainfall levels "rainfall" in country (*i*) time (*t*).
- **inter_h_rainfall:** Interaction effect between the dummy variable "high_rainfall_countr" and measures of rainfall levels "rainfall" in country (*i*) time (*t*).

2. The Global Precipitation Climatology Project (GPCP) database version 2.3 of monthly rainfall estimates, at 2.5 latitude and longitude degree intervals and cover the period 1979- 2015 (Adler et al., 2016). The GPCP data rely on a combination of actual weather station rainfall gauge measures and satellite information on the density of cold cloud cover, which is closely related to actual precipitation. The units of measurement are in millimeters of rainfall per day and are the average. The GPCP uses the Huffman (1997) method of data selection and merging, and how estimates of total yearly rainfall at the country-level have been produced see the Data set of MSS (2004), and for the calculation of total yearly rainfall/country measures from recently provided version 2.3 by GPCP, we determined grid nodes that fell within the national boundaries for our sample countries, otherwise, we assigned rainfall measures from the nearest nodes to their borders. For sub-Saharan Africa' countries, we used same nodes that were defined by MSS-2004 in Appendix A of the African Rainfall data set (A List of all nodes used in the calculation of rainfall data from the GPCP-V2.3 is in Appendix A1 to this document).

Derived variables for this data source are as follows

- **gpcp_neu:** Total yearly rainfall for country (*i*) is the average of the yearly rainfall estimates in millimeters on a resolution of 2.5 latitude/longitude degree nodes in the given country.

- **lag_gpcp_neu**: Lagged one year, with 0 for start of country series.
- **gr_gpcp_neu**: Growth in gpcp_neu: $(\text{gpcp_neu} - \text{lag_gpcp_neu})/(\text{lag_gpcp_neu})$, with 0 for start of country series.

Temperatures variables

- **temp**: The annual temperatures (Celsius degree) are computed by adding up all of the monthly observations in a given year divided by the number of months in that year.
- **temp_lag_1**: Temperature lagged one year.
- **temp_lag_2**: Temperature lagged two years.
- **gr_temp**: Growth in temperature from the previous year: $(\text{temp} - \text{temp_lag_1})/(\text{temp_lag_1})$.
- **gr_temp_lag_1**: Growth temperature lagged one year: $(\text{temp_lag_1} - \text{temp_lag_2})/(\text{temp_lag_2})$.

Climate Shocks

First, rainfall and temperature deviation variables are constructed using the following formula: $\text{dev.Xit} = (X_{i,t} - \bar{X}_i)/\sigma_i$

where $X_{i,t}$ is the annual rainfall or temperature in country i time t , and \bar{X}_i denotes to the long-term mean (35 years) for each country, and σ_i is the standard deviation for each country long-term (35 years) mean. The normalized annual temperature data ranges between -3.03, 3.18 deviation, has a mean of 0.03 and standard deviation of 0.98. While normalized annual rainfall data ranges from -2.69, 3.76 has a mean of almost zero and standard deviation of 0.99.

The defined climate derivation variables in the data set are as follows:

- **dev_rain** Annual rainfall deviation in a given country and year. $\text{dev_rain} = (\text{rainfall} - \text{rain_avg})/\text{rain_sd}$
- **dev_temp** Annual temperature deviation in a given country and year. $\text{dev_temp} = (\text{temp} - \text{temp_avg})/\text{temp_sd}$

In order to define if deviation in climate variables are positive or negative, we have generated dummies determining different thresholds (1 and 2) as follows:

- Rainfall deviation thresholds: takes four values; $\text{rain_dev_Threshold} = 1$ if dev_rain is $>$ than 1,
2 if $\text{dev_rain} > 2$,
3 if $\text{dev_rain} < -1$,
4 if $\text{dev_rain} < -2$, otherwise zero.

- Temperature deviation thresholds: takes four values; temp_dev_Threshold = 1 if dev_temp is > than 1,
2 if dev_temp > 2,
3 if dev_temp < -1,
4 if dev_temp < -2, otherwise zero.

Second, counting observed shocks (positive or negative) over previous 5-year period, to better understand the dynamics of shock thresholds

- R_pos_thresholds: Rainfall positive thresholds = (rain_dev_Threshold= 1 | rain_dev_Threshold= 2)
- R_neg_thresholds: Rainfall negative thresholds = (rain_dev_Threshold= 3 | rain_dev_Threshold= 4)
- count_R_pos_shock2Y: The number of observed positive rainfall shocks
= (12.R_pos_thresholds + 1.R_pos_thresholds)/2
- count_R_neg_shock2Y: The number of observed negative rainfall shocks
= (12.R_neg_thresholds + 1.R_neg_thresholds)/2
- T_pos_thresholds: Temperature positive thresholds
= (temp_dev_Threshold= 1 | temp_dev_Threshold= 2)
- T_neg_thresholds: Temperature negative thresholds
= (temp_dev_Threshold= 3 | temp_dev_Threshold= 4)
- count_T_pos_shock2Y: The number of observed positive Temperature shocks
= (12.T_pos_thresholds + 1.T_pos_thresholds)/2
- count_T_neg_shock2Y: The number of observed negative Temperature shocks
= (12.T_neg_thresholds + 1.T_neg_thresholds)/2

Third, to estimate the absolute impact of (combined) shocks over previous 5 years period on the interest variables in time t , without differentiating between positive and negative shocks, we have generated following variables:

- R_count_combShok=1: indicate number of observed rainfall shocks (experienced 1 year shock) over previous five years period.
- R_count_combShok=2: indicate number of observed rainfall shocks (2 shocks) over previous five years period.
- R_count_combShok=3: indicate number of observed rainfall shocks (3 shocks) over previous five years period.

- **R_count_combShok=4:** indicate number of observed rainfall shocks (4 shock shocks) over previous five years period.
- **R_count_combShok=5:** indicate number of observed rainfall shocks (5 shocks). It was exposed to climatic shocks in 5 consecutive years period.
- **R_count_combShok=1:** indicate number of observed rainfall shocks (experienced 1 year shock) over previous five years period.
- **T_count_combShok=2:** indicate number of observed temperature shocks (2 shocks) over previous five years period.
- **T_count_combShok=3:** indicate number of observed temperature shocks (3 shocks) over previous five years period.
- **T_count_combShok=4:** indicate number of observed temperature shocks (4 shocks) over previous five years period.
- **T_count_combShok=5:** indicate number of observed temperature shocks (5 shocks) over previous five years period.

Finally, moving average measurement that smoothes a data series by consolidating the yearly data points into a longer period of time, which is a mean of five years from t to $t-4$. Odusola and Abidoye (2015) has examined the impact of moving averages of climate variables and economic growth rate in Africa:

- **MA_rainfall:** smoothed average of rainfall variable in country i year t based on averages of the previous five years, including the given current year.
- **MA_gr_rainfall:** smoothed average of growth rainfall in country i year t based on averages of t to $t-4$ five years.
- **MA_temp:** smoothed average of annual temperature in country i year t based on averages of the previous five years, including the given current year (t to $t-4$).
- **MA_gr_temp:** smoothed average of annual temperature averages in country i year t based on averages of the previous five years, including the given current year (t to $t-4$).

Socio-Economic variables

1. Gross Domestic Product per capita

For the major economic variable GDP per capita, i.e. the total amount of goods and services produced in the economy, divided by its population, there is no complete time series for our sample (59 countries) from 1980 to 2015 such as the World Development Indicators

source. However, we have estimated with data on this variable from two different sources; (i) James et al. (2012) has developed a comprehensive time series of GDP per capita for 210 countries from 1950 to 2015, which covers the time period and countries exist in our study. In their time series GDP per capita estimates expressed in either constant US dollar terms or international dollar terms (corrected for purchasing power parity) from seven sources to derive in the end two new GDP per capita series (the base year 2005). (i) From James et al. (2012) study, we include GDP per capita indicator (In international (ID) and constant (USD) dollar), its derived variables as follows:

- **gdp_c_id:** GDP per capita in international dollar terms (ID).
- **gdp_c_id_lag_1:** GDP per capita (ID) lagged one year.
- **gdp_c_id_lag_2:** GDP per capita (ID) lagged two years.
- **gr_gdp_c_id:** changes in GDP per capita (ID) from the previous year: $(\text{gdp_c_id} - \text{gdp_c_id_lag_1}) / (\text{gdp_c_id_lag_1})$.
- **gr_gdp_c_id_lag_1:** GDP growth (ID) lagged one year: $(\text{gdp_c_id_lag_1} - \text{gdp_c_id_lag_2}) / (\text{gdp_c_id_lag_2})$.
-
- **gdp_c_usd:** GDP per capita in constant US dollar terms (USD).
- **gdp_c_usd_lag_1:** GDP per capita (USD) lagged one year.
- **gdp_c_usd_lag_2:** GDP per capita (USD) lagged two years.
- **gr_gdp_c_usd:** changes in GDP per capita (USD) from the previous year: $(\text{gdp_c_usd} - \text{gdp_c_usd_lag_1}) / (\text{gdp_c_usd_lag_1})$.
- **gr_gdp_c_usd_lag_1:** GDP growth (USD) lagged one year: $(\text{gdp_c_usd_lag_1} - \text{gdp_c_usd_lag_2}) / (\text{gdp_c_usd_lag_2})$.
- **basis_gdp_id_1981:** GDP per capita in international dollar terms at the beginning of period analysis, 1981 (1991 for Namibia).
- **basis_gdp_usd_1981:** GDP per capita in constant US dollar terms at the beginning of period analysis, 1981 (1991 for Namibia).

(ii) The second source is the database of UNSD (2020), which provides a complete and consistent set of GDP per capita time series from 1970 onwards, from the main National Accounts aggregates of all UN Members States and other territories in the world for which National Accounts information is available, GDP per capita estimates expressed

either in current or constant price-US dollars: <http://data.un.org/>

Derived variables are as follows

- **gdp_c_cur:** GDP per capita estimates expressed in current price-US dollars.
- **gdp_c_cur_lag_1:** GDP per capita estimates expressed in current price-US dollars lagged one year.
- **gdp_c_cur_lag_2:** GDP per capita estimates expressed in current price-US dollars lagged two years.
- **gr_gdp_c_cur:** Changes in GDP per capita estimates expressed in current price-US dollars from previous year:
 $(\text{gdp_c_cur} - \text{gdp_c_cur_lag_1}) / (\text{gdp_c_cur_lag_1})$.
- **gr_gdp_c_cur_lag_1:** GDP growth in current price-US dollars lagged one year: $(\text{gdp_c_cur_lag_1} - \text{gdp_c_cur_lag_2}) / \text{gdp_c_cur_lag_2}$.
- **gdp_c_con:** GDP per capita estimates in constant price-US dollars.
- **gdp_c_con_lag_1:** GDP per capita estimates in constant price-US dollars lagged one year.
- **gdp_c_con_lag_2:** GDP per capita estimates in constant price-US dollars lagged two years.
- **gr_gdp_c_con:** Changes in GDP per capita estimates expressed in constant price-US dollars from previous year:
 $(\text{gdp_c_con} - \text{gdp_c_con_lag_1}) / (\text{gdp_c_con_lag_1})$.
- **gr_gdp_c_con_lag_1:** GDP growth estimates in constant price-US dollars lagged one year: $(\text{gdp_c_con_lag_1} - \text{gdp_c_con_lag_2}) / (\text{gdp_c_con_lag_2})$.

2. Food production index variable food_index: The aggregate volume of agricultural production for each year compared to the base period 2004-2006, covers food crops that are considered edible and that contain nutrients. Coffee and tea are excluded because, although edible, they have no nutritive value, from the **Food and Agriculture Organization of the United Nations (2016)**.

3. Oil exporter status variables

- **oil_exp_wdi:** Oil exporter status (% of merchandise exports) using time series cover our sample countries from **the World Bank (2016)**.

- **oil_exp_wdi_lag_1:** Oil exporter status lagged one year.
- **oil_exp_wdi_lag_2:** Oil exporter status lagged two years.
- **gr_oil_exp_wdi:** changes in oil exporter status from the previous year:
 $(oil_exp_wdi - oil_exp_wdi_lag_1) / (oil_exp_wdi_lag_1)$.
- **gr_oil_exp_wdi_lag_1:** growth of oil exporter lagged one year:
 $(oil_exp_wdi_lag_1 - oil_exp_wdi_lag_2) / (oil_exp_wdi_lag_2)$.

4. Total merchandise trade variable

- **trade_exports:** Total merchandise trade of a country exports to the world in US dollar at current prices using time series from the The World Trade Organization (2016).
- **trade_exports_lag_1:** Total merchandise trade of a country exports to the world in US dollar at current prices lagged one year.
- **trade_exports_lag_2:** Total merchandise trade of a country exports to the world in US dollar at current prices lagged two years.
- **gr_trade_exports:** Changes in total merchandise trade of a country exports to the world in US dollar at current price from previous year: $(trade_exports - trade_exports_lag_1) / (trade_exports_lag_1)$.
- **gr_trade_exports_lag_1:** Growth in total merchandise trade lagged one year:
 $(trade_exports_lag_1 - trade_exports_lag_2) / (trade_exports_lag_2)$.

Demographic indicators

1. Population

- **population_sh:** Total indicator in thousands counts all residents regardless of legal status or citizenship. The source of this data is **the World Bank (2018)**.
- **population_sh_lag_1:** Total population lagged one year. **population_sh_lag_2:** total population lagged two years.
- **Urban_pop:** Expressed as a percentage of the total population.

2. Education and unemployment

- **educ_attainment:** The percentage of educational attainment at least completed primary (ISCED 1 or higher), population > 25 years for both sexes. From UNESCO Institute for Statistics (2008) ¹⁵.

¹⁵The UNESCO Institute for Statistics. <http://data.uis.unesco.org/>

- **unempl_inter_edu:** Unemployment with intermediate education (% of total labour force with basic education) from **World Bank (2016)**

Fractionalization variables For measuring ethnic and religious fractionalization, we use fractionalization's index, provided by Alesina et al. (2003), and computed using the formula $FRAC_m = 1 - \sum_{i=k}^N S_{km}^2$, where S_{km} is the share of group k in country m .

- **ethnic_sh:** For the ethnic variable data on various ethnic groups that were disaggregated, combined from several sources, however, the primary source is Encyclopaedia Britannica (2001), in addition to the Central Intelligence Agency (CIA, 2000; Levinson, 1998), and the Minority Rights Groups International (Thornberry et al., 1997).
- **ethnic_sh_lag_1:** Ethnic data lagged one year.
- **ethnic_sh_lag_2:** Ethnic data lagged two years.
- **religion_sh:** Religious data is based exclusively on data from **Encyclopaedia Britannica, 2001**.
- **religion_sh_lag_1:** Religious data lagged one year.
- **religion_sh_lag_2:** Religious data lagged two years.

Political variables

- **polityiv_sh:** Type of political regime for each country on a range from -10 (full autocracy) to +10 (full democracy). Regimes that fall into the middle of this spectrum are called anocracies. The source is the project of Roser (2019), based on Polity IV Project (2013) and Wimmer and Min (2006).
- **polityiv_sh_tr:** We transformed Polity IV scores (polityiv_sh) to be instead on a range from 1 to 20, for easier interpretation of coefficients.
- **polityiv_sh_tr_lag_1:** Transformed Polity IV scores (polityiv_sh_tr) (range from 1 to 20) lagged one year.
- **polityiv_sh_tr_lag_2:** Transformed Polity IV scores (polityiv_sh_tr) (range from 1 to 20) lagged two years.
- **strength_gr_polityiv:** We constructed this variable to observe the absolute strength of the political crisis in a given country and year compared to the previous year. It indicates changes from the previous year in absolute

terms of Polity IV scores either toward democracy or backward to autocracy.
 $\text{strength_gr_polityiv} = |\text{polityiv_sh_tr} - \text{polityiv_sh_tr_lag_1}|$

Voice and Accountability indicator

- **accountab:** Percentile rank among all countries (ranges from 0=lowest to 100=highest rank), reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well freedom of expression, association, and a free media. The source is World Bank (2014) covering time from 1960 to present.

Natural conditions

- **agri_land:** Agricultural land (% of land area) refers to the share of land area that is arable as defined by the FAO, under permanent crops, and under permanent pastures. Land abandoned as a result of shifting cultivation is excluded. **The source is World Bank (2016).**
- **arable_land:** Arable land (hectares per person).
- **mountains_sh and log_mountains_sh:** the proportion of mountainous terrain and its logarithmic value. We kept most mountainous terrain data of Miguel et al. (2004), but we complete our new data base (i.e. the rest of countries and years) by data of Fearon and Laitin (2003), who formed their data with respect to the geographer Gerrard (2014).
- **area.km2** The total area of a country in km^2 .
- **Latitude:** GeoDist provides useful data incorporates country-specific geographical variables, including geographical coordinates of their capital cities (CEPII, 2020).

We have included information of the water use variable from FAO (2017a), which is classified into sub-variables (i) pressure on water resources for following sub-sub-variables:

- **freshwater** Freshwater withdrawal (MDG 7.5.) as % of total renewable water resources.
- **agri_renew** Agricultural water withdrawal as % of total renewable water resources (%).
- **water_stress** Aggregated indicator (SDG 6.4.2.) freshwater withdrawal as a proportion of available freshwater resources. This indicator is also known as water withdrawal intensity.

- **wasser__total** Annual level of freshwater withdrawal, calculated averagely over each decade (roundly 1980-1989, 1990-1999, 2000-2017), in $10^9 \text{ m}^3/\text{year}$.
- **water__1km2** The average annual level of freshwater withdrawal (calculated averagely over each decade) divided by country area
water__1km2 = $10^6 \times \text{wasser__total}/\text{area.km2}$, in $10^3 \text{ m}^3/\text{km}^2$.