Internal Conflicts and Shocks. A Narrative Meta-Analysis

March 2023

Abstract

Do income shocks locally affect internal conflicts? To address this question, this paper employs a meta-regression analysis of 2,464 infranational estimates from 64 recent empirical studies on conflicts and income-related shocks in developing countries. After accounting for publication selection bias, the analysis finds that, on average, income-increasing shocks in the agriculture sector are negatively associated with the local risk of conflict. Nonetheless, the analysis finds no average effect of income-decreasing shocks in the agriculture sector or income-increasing shocks in the extractive sector on the local risk of conflict. The paper also shows that studies that fail to uncover empirical effects that conform to researchers' expectations on the theoretical mechanisms are less likely to be published. Differences in the geographical area of study, the choice of control variables, and the way shocks are measured substantially explain the heterogeneity among estimates in the literature.

Keywords: Conflicts; climate shocks; commodity shocks; natural resources; income-driven conflicts; meta-regression analysis

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1 Introduction

By 2030, up to two-thirds of the world's extremely poor people are expected to live in countries affected by violence and conflict (World Bank, 2020). In other words, contexts combining extreme poverty and exposure to conflict may become more common in the upcoming years. While there is little doubt about the damaging consequences of conflict on development (see for example Abadie and Gardeazabal, 2003; Islam et al., 2016), the effect of local economic conditions (i.e. incomes and economic prospects) on the risk of conflict is subject to academic discussion about the explanatory mechanisms and the appropriate empirical strategies to model them (Bazzi and Blattman, 2014; Laville, 2019). Understanding how incomes and economic prospects locally affect the risk of conflict is therefore important in order to provide adequate policy recommendations to low to intermediate income countries concerned about "conflict traps"[1] and exposed to income shocks related to climate change and commodity price disruptions.

Low levels of national incomes are consistently associated with higher risks of internal conflicts in empirical studies (Hegre and Sambanis, 2006; Blattman and Miguel, 2010). However, determining the direction of the causal relationship is challenging, particularly at the sub-national level. The long-term negative impacts of insecurity on economies and institutions could influence the direction of the relationship, and aggregated measures of poverty may not accurately reflect the economic constraints faced by individuals in conflict-affected areas (Corral et al., 2020; Laville, 2019). Obtaining micro-level data through field surveys is also limited due to security concerns (Axinn et al., 2012), and other individual considerations that are difficult to quantify may also be at play (Cramer, 2002). Recent studies have used conflict location data and satellite imagery to better understand the local contexts in which violence develops. By focusing on small spatial units and georeferenced data, such as grid-cells, researchers can introduce key sources of heterogeneity at the local scale - such as the location of mineral deposits or the volume of production/exports in each area (Maystadt

[1] In essence, the idea that civil war begets more civil war (Collier, 2003).

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et al., 2014; Berman et al., 2017; Dube and Vargas, 2013; McGuirk and Burke, 2020) -, which can be exploited using quasi-experimental frameworks to isolate and test the validity of specific mechanisms (Blattman and Miguel, 2010; Couttenier and Soubeyran, 2015; Laville, 2019). For instance, recent studies on conflicts in Sub-Saharan Africa using grid-cells and georeferenced data show that positive income shocks decrease conflict probability in the cell, while negative income shocks increase the risk of conflict (Berman and Couttenier, 2015; von Uexkull, 2014). However, these studies present key methodological differences in the sign and proxies used to define the shock, making it challenging to establish income as a key local factor of conflict.

Figure 1 presents the distribution of the t-students from 1,397 direct estimates on income shocks and conflicts from the literature. Figure 1a shows that the literature associates almost twice as often income changes with adverse rather than positive effects on conflict, suggesting a possible asymmetric research focus on the link between income and violence. In Figure 1b, we adjust the t-students so that the *ex-ante* assumed effects all work in the same direction.[2] It reveals that finding a result in line with *ex-ante* expectations is twice more frequent (67.4% of estimates) than finding one with an unexpected signs (32.5% of counter-intuitive or null effects). This coincidence between the obtained and expected results may suggest the presence of genuine effects or manipulations by researchers, namely, publication selection bias (i.e., to prefer results with signs consistent with their expectations or prior understanding, or results with higher statistical significance).

To analyze these methodological concerns and assess the presence of publication selection bias in the literature, we perform a meta-regression analysis (MRA) on 2,464 estimates from 64 studies (including 1,397 direct or unconditional estimates) published between 2010 and 2021. The MRA is a regression on estimates from existing regressions. In contrast to simple meta-analysis, this statistical method aims to highlight one or more study characteristics

[2] We reverse the sign of t-statistics for regressions focusing on theoretically pacifying mechanisms as they are the only channels with an *ex-ante* expectation of reducing risks of conflicts.

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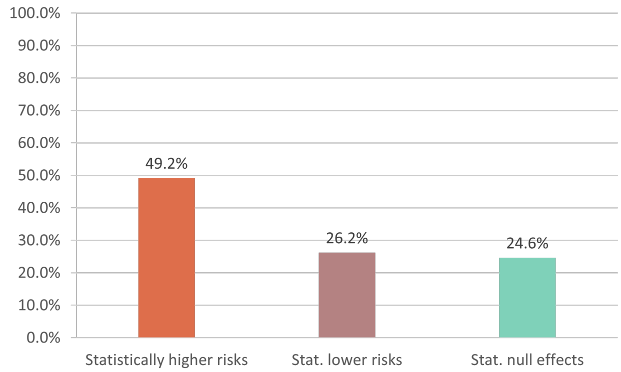
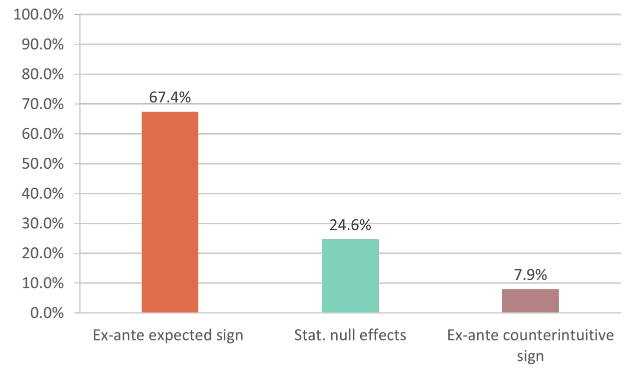


(a) t-students



(b) Adjusted t-students

Notes: Distribution of the t-statistics taken from 1,397 estimates from 61 studies (three studies in our sample of 64 selected studies do not present unconditional estimates). A positive (negative) statistically significant t-student suggests that the estimate shows a statistically higher (lower) risk of conflict. A positive (negative) adjusted t-student signifies that the estimate statistically present (does not present) the expected sign. We consider a risk error of 10%, so t-student $\geq$ 1.645 (or $\leq$ -1.645). All other t-statistics are reported in the "*Statistically null effects*" category. *Source: Authors' compilation from MRA database.*

Figure 1: Distribution of the t-students and Adjusted t-students

that may explain heterogeneity among estimates from selected studies. In other words, the MRA objective is to summarize and "make sense" of statistical heterogeneity (i.e., the true effects in each study not being identical) on a given topic in the literature (Thompson and Higgins, 2002; Balima et al., 2020). As estimates within the same study are likely to be interdependent (Balima et al., 2020), we use a multilevel model to account for both between study heterogeneity and within-study dependance. Also, following the guidelines by Stanley and Doucouliagos (2012), the MRA distinguishes the genuine multidimensional effects of income shocks on internal conflicts from the potential publication bias inherent to most economic fields (Doucouliagos and Stanley, 2013). We develop a methodological approach in three steps to assess the effect of various transmission channels and take into account the heterogeneity derived from different empirical methodologies. First, a representative sample of empirical studies is built (called the meta-sample henceforth). Second, all the estimated coefficients from these selected studies are collected. Third, we assess the presence of publication selection bias and genuine effects from the collected estimates and explore the drivers of heterogeneity among them.

MRA can identify and accommodate publication selection bias, which arises when re-

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searchers, editors or reviewers choose to report or publish empirical estimates that conform to their expectations (type I publication selection bias) or that are statistically significant (type II publication selection bias) (Mandon and Woldemichael, 2023). We find that the present literature suffers from the two types of publication bias: researchers tend to prefer studies that (i) find higher risks of conflicts when they focus on negative agricultural shocks (type I bias); and (ii) promote results with higher statistical significance (type II bias). After filtering them out, we report the presence a genuine negative effect of positive agricultural shocks on conflicts. We also provide evidence that the section of the literature studying adverse or unspecified mechanisms favors empirical results showing a higher risk of conflict, independently of the sector of the economy affected by the shock.

This study is, to our knowledge, the first MRA covering the literature on the effect of income shocks on the risk of conflicts. Previous meta-analyses have examined how the risk of conflict responds to natural resource endowment (O'Brochta, 2019; Vesco et al., 2020), commodity price shocks (Blair et al., 2021), and climate change (Hsiang et al., 2013, 2014).[3] The present meta-analysis aims to reconcile all these different approaches through the prism of income shocks; as highlighted by recent literature reviews (Couttenier and Soubeyran, 2015; Laville, 2019), natural resource endowment, (commodity) price shocks and climate change could affect the risk of conflicts through income shocks both for active (or potential) warring groups and individuals. Furthermore, scholars have repeatedly expressed concerns about the presence of biases (including the publication selection bias) in the conflict literature due to the great variety of tested mechanisms, outcomes and empirical strategies (Ioannidis, 2005; Dixon, 2009; Bazzi and Blattman, 2014), the selection of control variables according to

[3]The link between climatic events and violent intergroup conflict found by Hsiang et al. (2013) has been subject to some criticism, leading them to publish reply in a second article (Hsiang et al., 2014). Buhaug et al. (2014) argue that the sample studies are not fully independent, and there is considerable overlap between them, which makes the calculation of climate effects unrealistic. Additionally, the sample of "intergroup conflict" studies covers a wide range of social phenomena, climatic events, and spatial scales, making it challenging to generalize the findings. Finally, they question the sample's representativeness given the lack of studies revisiting previously investigated climate-conflict associations.

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statistical significance and not theory (Ward et al., 2010), or the fragility of published results in studies conducted at the country/year level (Hegre and Sambanis, 2006; Ward et al., 2010). This work takes up several of these criticisms and determines whether they are justified in the context of work done at the sub-national scale on income shocks and conflicts.

The paper is organized as follows. Section 2 presents the different mechanisms linking income shocks to conflicts according to the literature. Section 3 discuss the construction of the meta-sample. Section 4 deals with publication bias. Section 5 explores different sources of heterogeneity in the collected estimates. Section 6 summarizes our findings and concludes.

2 Review of the Mechanisms Involved in the Literature

Among all the possible channels of transmission between local incomes and conflicts, the literature emphasizes the role of *opportunity cost* and *rapacity* (Blattman and Miguel, 2010; Couttenier and Soubeyran, 2015).[4] The *opportunity cost* mechanism posits that lower wages in productive sectors of the economy increase relative gains from violent appropriation, which lowers the opportunity cost of conflict and increases the risk of predatory behaviors (Grossman, 1991; Hirshleifer, 1995; Collier, 1998). The *rapacity* effect states that a rise in contestable income increases the risk of conflict by raising gains from appropriation. Put differently, rising commodity prices increase the rent from their capture and the taxes collected in production areas, facilitating the financing and recruitment capabilities of armed groups (Reuveny and Maxwell, 2001; Collier et al., 2008) and increasing their capacity to sustain a rebel movement (Berman et al., 2017).[5] In sum, a positive income-increasing shock, typically a higher selling price for a given produced commodity, could both increase conflict through

[4] A third mechanism, the *state capacity*, posits that adverse income shocks expose the state to negative growth, which constrains investment in national counterinsurgency capacities (Fearon and Laitin, 2003). This channel appears however off the scope of this paper since it takes place at the national level and/or supposes that the state largely finance its operations by collecting tax revenues locally (which is a strong hypothesis for many low to intermediate income countries).

[5] Other channels of transmission have been investigated by the literature, like separatist ambitions in resource-rich regions (Morelli and Rohner, 2015), lower incentives to develop sufficient state capacity to discourage or buy off rebellion in rentier and resource-dependent states (Fearon, 2005), and grievances from environmental degradation and lack of mining jobs (Ross, 2004).

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rapacity effects, or decrease it through the opportunity cost mechanism. This comes from the fact that these shocks can simultaneously affect wages and returns to conflict. In a simple general equilibrium model, Dal Bó and Dal Bó (2011) predict that a key consideration in determining whether an income shock will increase or decrease the risk of conflict is the nature of the economic sector where it occurs. They find that positive shocks to labor-intensive industries diminish the risk of conflict, while positive shocks to capital-intensive industries increase the risk. A shock to a capital-intensive sector expands the capital-intensive industry and contracts the labor-intensive one. As a result, labor is relatively less scarce, resulting in lower wages and lower costs of appropriation activities relative to the amount of appropriable resources. Empirical evidence supports their findings. In Colombia, Dube and Vargas (2013) find that a rise in the price of coffee, a labor-intensive commodity, decreases violence in production areas, while a rise in the price of oil, a capital-intensive commodity, increases violence. They explain these results by the variation in wages affecting the opportunity cost of conflict, and by the rapacity of armed groups seeking to capture the higher oil rents. Fjelde (2015) and Berman and Couttenier (2015) also find results in line with the opportunity cost channel for labor-intensive agricultural commodities produced in Africa.

Recent empirical evidence suggests that the opportunity cost is not an exclusive transmission channel for labor-intensive goods, nor is rapacity exclusive to capital-intensive goods. Commodities' lootability and producers' taxation opportunities can also influence the nature of transmission channels. Rapacity can be a relevant transmission channel for labor-intensive export resources if armed groups can tax producers. In Colombia, Angrist and Kugler (2008) show that the increase in the world price of cocaine (whose production is labor intensive) in the 1990s did increase the quantity produced but had a modest impact on producers' incomes. Indeed, the wealth created was captured by armed groups and the number of violent events increased in the producing regions. Crost and Felter (2020) also find a higher risk of conflict when the price of bananas (a high-value exported commodity) increases. In the Democratic Republic of Congo, Sánchez de la Sierra (2020) finds that positive demand shocks on coltan,

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a labor-intensive mineral, increase violence and suggests that the effect of the opportunity cost channel can be overridden by a taxation-induced rapacity effect.

Income shocks can also have different effects on the risk of conflict when they impact producers or consumers. In Sub-Saharan Africa, McGuirk and Burke (2020) find that higher commodity prices reduce conflict over the control of territory (what they call "factor conflict") in food-producing areas, and increase conflict over the appropriation of surplus ("output conflict") in food-consuming areas. Using survey data in Nigeria, Abidoye and Calì (2021) find that higher prices of consumed goods increase the risk of conflict by reducing consumers' incomes (in line with the opportunity cost channel), while higher oil prices increase the risk of conflict in oil-producing areas (in line with the rapacity effect). Concerning less organized and violent forms of collective actions, a large body of empirical research finds that food prices can act as a trigger for urban riots and social unrest (Bush, 2010; Bellemare, 2015; Hendrix and Haggard, 2015). They generally assume that relative deprivation and grievances are the main explanatory channel, although it is difficult to provide empirical evidence of causality (Martin-Shields and Stojetz, 2019). Another explanatory mechanism is the breakdown of state authority and legitimacy when it fails to provide food security (Arezki and Brueckner, 2014; Buhaug et al., 2015).

3 Construction of the Meta-Sample

3.1 Studies' Collection Strategy and Inclusion Criteria

We identified 565 potentially relevant studies (the identification process is detailed in the Online Appendix): 22 from literature reviews, 138 from meta-analyses, and 405 from keyword searches. To ensure sample coherence, we applied seven inclusion criteria: we selected studies published in peer-reviewed academic journals between 2010 and 2021,[6] reporting exploitable empirical results, where the outcome variable is the onset, incidence, or duration of a form of

[6]We therefore exclude working papers that may be of high quality in terms of content but have not been subjected to the peer review process.

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internal conflict,[7] and where units of analysis are sub-national. We included studies analyzing at least one income-related channel of transmission and conducted in one or more non-OECD's high-income countries before the Cold War.[8] Our final sample comprised 64 studies meeting these criteria.

3.2 Estimates Collection

For each selected study, we collect estimates of the effect of income-related shocks, as well as information on the shock itself, the conflict variable used, the size and composition of the sample, the estimation techniques, the level of aggregation of spatial units, the covariates used, the publication year and formats, and other relevant information for the MRA. From the 64 studies selected, we collect 1,397 direct estimates and 1,067 conditional (or interactive) estimates.

[7] We excluded analysis of conflict intensity (i.e., number of fatalities) to limit causal heterogeneity between studies, as such analyses refer to different explanatory mechanisms (see, for example, Lacina, 2006).

[8] See, `https://www.oecd.org/about/document/ratification-oecd-convention.htm`.

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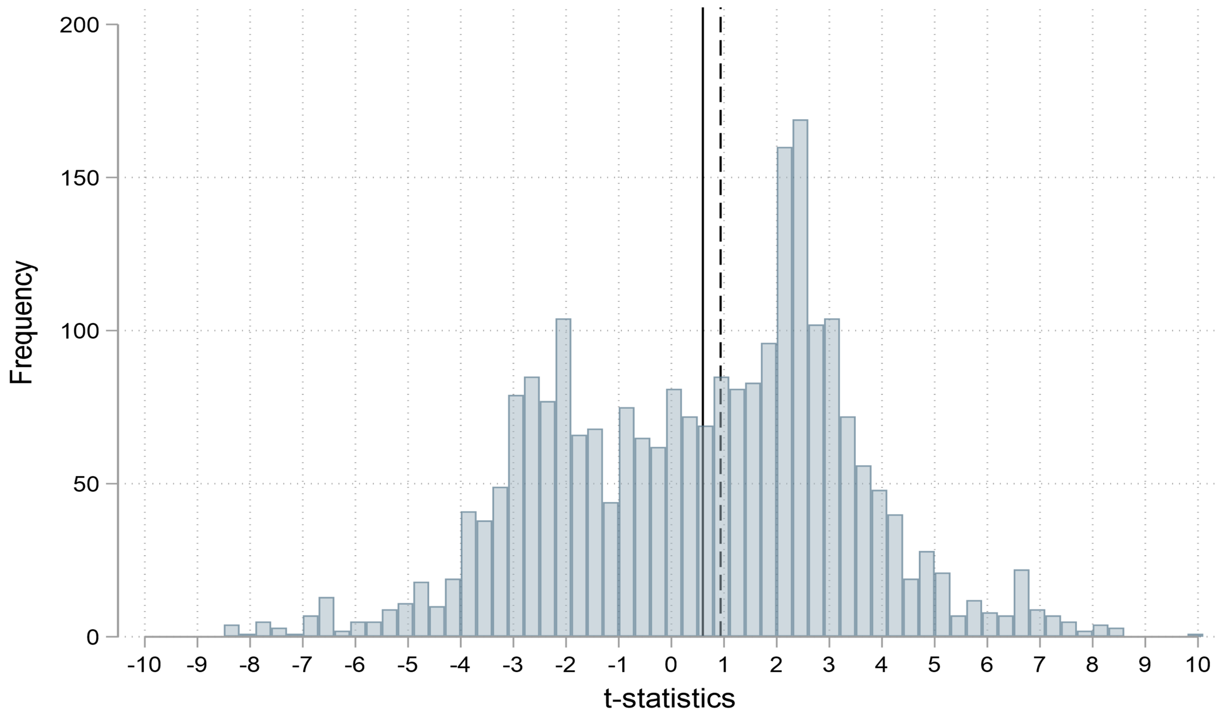

Notes: The solid line shows the mean of reported t-statistics; the dashed line denotes the mean of the median estimates of the study. To ensure the figure's readability, absolute t-statistics higher than 10 (0.6% of the observations) and below -10 (0.3% of the observations) are not presented. *Source: Authors' compilation from MRA database.*

Figure 2: Distribution of T-Statistics

Figure 2 plots the distribution of the values of t-statistics used in the collected estimates. As we selected studies analyzing either positive or negative shocks, we observe two spikes in the distribution, one around -2 and one around 2 (i.e. the statistical significance threshold or 5%). Positive t-statistics are slightly more frequent (59% of the observations), which explains why the mean and median values are 0.6 and 0.9. Of the t-statistics, 22% are below -2 and 36% are above 2. Values exceeding 10 or inferior to -10 only represent 0.9% of the sample, with minimum and maximum values of -27.7 and 46.8. To prevent potential distortions caused by the presence of outliers, we winsorize t-statistics and degrees of freedom at the top and bottom of 5% level (Lipsey and Wilson, 2001; Viechtbauer and Cheung, 2010).[9]

[9] Winsorisation corrects biases linked to extreme values without losing observations. It consists in replacing the outliers by the highest values in given percentiles.

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3.3 Grouping the Collected Estimates According to Their Main Transmission Channels

The collected estimates test the relationship between the risk of internal conflict and different types of positive or negative shocks. As a result, our meta-sample is heterogeneous in terms of the variables of interest and the transmission channels implicitly tested by the authors. Analyzing this raw sample would complicate the interpretation of the MRA's results and limit our contributions to two central debates in conflict economics, namely what economic mechanisms are at play and how to test them empirically. We therefore split the collected estimates into four meta-regression subgroups that differ in the direction of the shock (wealth increasing or decreasing) and the sector of activity that is affected (agriculture, extractive or other sectors). Indeed, the literature suggests that income shocks affecting the extractive or the agriculture sector do not refer to the same main channel of transmission (Dal Bó and Dal Bó, 2011). The first group, ***Negative Agricultural Shock*** (**AS-**), contains all estimates of negative transitory agricultural shocks (e.g., droughts, floods, rain deficiencies, etc.). The second one, ***Positive Agricultural Shock*** (**AS+**), includes all estimates of positive transitory agricultural shocks (e.g., increased demand and international prices for the cultivated good, environmental conditions particularly suitable to its production, etc.). The third group, ***Positive Hydrocarbon/Mineral Shock*** (**HS+**), contains all estimates of transitory shocks on extractive goods (i.e., hydrocarbon and minerals), including increases of the international price of the resource and subsidies to mining concessions. The other estimates fall into the heterogeneous category ***Other Shocks***, which includes estimates of (positive or negative) pure climatic shocks that are not explicitly related to agriculture, labor market shocks, financial crisis, or shocks to the drug sector.

Following the literature, we may expect shocks affecting the agriculture sector to mainly test poverty related mechanisms (notably, the opportunity cost channel) as they affect more labor-intensive commodities and as rapacity effects concern a specific subset of high-value agricultural exports. Alternatively, we may expect shocks affecting the extractive sector to

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mainly test rapacity channels as they focus on more capital-intensive commodities. As a matter of fact, Table 1 confirms our expectations. Of the 710 estimates focusing on positive agricultural shocks, 550 (77.5%) test poverty-related mechanism and 151 (22.1%) test rapacity effects. Of the 1,049 estimates focusing on negative agricultural shocks, 896 (85.4%) test poverty-related mechanism and only 5 (0.5%) test rapacity effects, and 139 (13.3%) test other channels of transmission (including 107 cases of regional destruction).

Table 1: Main Implicitly Tested Mechanism in Estimates According to their Meta-Regression Subgroup

	Agricultural shock (+)	Agricultural shock (-)	Hydrocarbon/Mineral shock (+)	Other shock (+ or -)	Total
Type of mechanism					
Poverty-related	550	896	82	46	1,574
Rapacity-related	151	5	423	4	583
Other	4	139	38	0	181
Non specified	5	9	0	112	126
Total	710	1,049	543	162	2,464

Notes: Number of estimates in the total sample of 2,464 estimates. Poverty-related mechanisms include the dynamism of local economy, food scarcity, budget constrains and water insecurity. Rapacity-related mechanisms include rent capture and the funding of insurgents. Other mechanisms include exodus, grievance, imperfect information, regional destruction (incl. agricultural soils) and state capacity. *Source: Authors' compilation from MRA database.*

Figure 3 presents the proportion of collected estimates in each meta-regression subgroup. Our three main subgroups (AS-, AS+, and HS+) account for 90.3% of the baseline sample of 1,397 regressions and 67% of the baseline estimates concern agricultural shocks (71.4% of the total sample of 2,464 regressions). Other shocks only account for 6.5% of the total sample. Detailed information on the types of shocks in each meta-regression subgroup is provided in Figure A1, Table A1, and in the Online Appendix.

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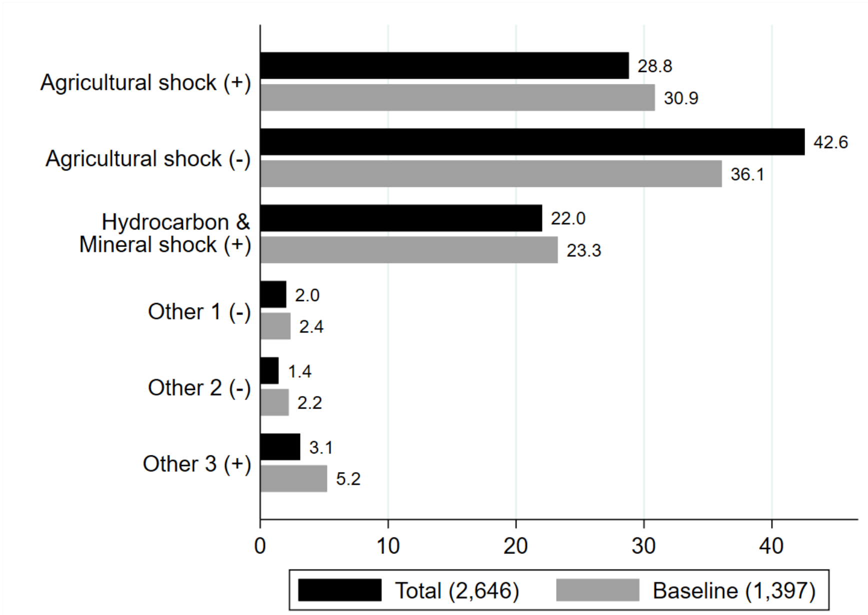

Notes: Black bars represent the percentage of the total sample (2,464 estimates), while gray bars represent the percentage of the baseline sample (1,397 estimates). Other categories include negative pure climatic shocks (Other 1), labor market shocks, financial crisis, drug sector shocks (Other 2), and positive pure climatic shocks (Other 3). *Source: Authors' compilation from MRA database.*

Figure 3: Distribution of Estimates According to their Meta-Regression Subgroup

4 Publication Selection Bias and Genuine Effects

Publication selection is a common phenomenon in empirical studies that can be broadly defined as the process of selecting research papers or estimates for their statistical significance (Stanley and Doucouliagos, 2012). When this bias is substantial, it can distort statistical inference and any resulting understanding of research as more significant effects are over-represented in the published literature (Stanley and Doucouliagos, 2012). There are two types of publication selection bias. Type I bias is the tendency to prefer results whose signs are consistent with expectations or prior understanding, and type II bias is the tendency to prefer results with higher statistical significance, regardless of their sign (Mandon and Woldemichael, 2023). Publication selection bias can arise due to several patterns intrinsic to empirical research, including editors' predisposition to accept papers consistent with the conventional view and/or presenting highly significant results, as well as researchers' self-

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censoring attitudes and tendency to select their models based on conventionally accepted results (Card and Krueger, 1995; Stanley and Doucouliagos, 2012). By filtering these publication biases, we can determine, if any, the "true effect" (or "genuine effect") of income shocks on the risk of internal conflict.

4.1 Method

The unit of observation in this MRA is the estimate/regression, given that it presents notable difference with other regressions. As a result, estimates within the same study are likely to be interdependent (Balima et al., 2020). As in Balima et al. (2020) and as recommended by Doucouliagos and Laroche (2009) and Doucouliagos and Stanley (2009), we employ a multilevel model to account for both (i) heterogeneity at the study/paper level, and (ii) heterogeneity at the estimate/regression level. The multilevel model is precisely called the multilevel random effect model, due to the introduction of random effects for each study, and these random effects control for the interdependence of estimates within studies, also called within-study dependence (Balima et al., 2020). The model is displayed as follow in Equation 1:

$$effect_{ij} = \beta_1 + \beta_0 SE_{ij} + \lambda_j + \epsilon_{ij} \tag{1}$$

where $effect_{ij}$ refers to the coefficient of income shocks on conflicts from the i^{th} regression or estimate of the j^{th} study or paper encompassed in our MRA; SE_{ij} denotes the standard error of the associated effect from the i^{th} estimate of the j^{th} study. λ_j stands for the study level random effect and ϵ_{ij} is a disturbance term, adjusted for study level (and channels of transmission level) clustering. The absence of any statistical association between the effect and its standard error ($\hat{\beta}_0 = 0$) would indicate the absence of publication selection bias of type I and type II. By contrast, the coefficient β_1 captures the effect of income shocks on conflicts beyond the potential publication selection bias, and it is often referred to as the 'true value' or the genuine effect of income shocks on conflicts. In other words, rejecting $\hat{\beta}_1 = 0$

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would indicate the presence of an empirical positive or negative effect of income shocks on conflicts beyond the publication bias.

Dividing Equation 1 by SE_{ij} leads to Equation 2. Such an operation enables us to control for heteroscedasticity due to differences across studies (e.g., sample size, models used by scholars):

$$t_{ij} = \beta_0 + \beta_1 \frac{1}{SE_{ij}} + \frac{\lambda_j}{SE_{ij}} + \varepsilon_{ij} \tag{2}$$

This model stands for the 'Funnel Asymmetry Test - Precision Effect Test' (FAT-PET). t_{ij} stands for the t-values associated with the coefficient of income shocks on conflicts from the i^{th} estimate of the j^{th} study encompassed in our MRA. The intercept (β_0) tests for the presence (or absence) of type I and type II publication bias, and, as in Equation 1, the coefficient β_1 tests for the presence or absence of an effect beyond the publication bias.

Our MRA focuses on the link between positive and negative income shocks, hence on estimates with likely opposite signs. To ensure comparability of estimates, we replace the left-hand side of Equation 2 with the absolute t-student value and consider alternatively adjusted t-student values: we reverse the signs of t-statistics for regressions focusing on pacifying mechanisms as they are the only channels with an *ex-ante* expectation of reducing risks of conflicts. This gives us Equation 3:

$$|t_{ij}| = \beta_0 + \beta_1 \frac{1}{SE_{ij}} + \frac{\lambda_j}{SE_{ij}} + \varepsilon_{ij} \tag{3}$$

Testing the null hypothesis ($\beta_0 = 0$) in Equation 3 assesses the presence of type II publication selection bias. To check the presence of a "genuine" effect after filtering out potential publication bias, we follow Stanley and Doucouliagos (2012) and carry out the so-called Precision Effect Test (PET). Concretely, we test the null hypothesis that the parameter associated with the inverse standard error (β_1) in Equation 2 equals zero. In other terms, we test whether in Equation 1, the intercept (β_1 or genuine effect) has a statistically significant

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role regardless of the outcome of the publication selection bias (influence of $\beta_0 SE_{ij}$). Rejecting the null hypothesis would thus signal that a genuine effect remains after filtering out the publication bias.

In addition to the FAT-PET procedure, we estimate the bias-adjusted genuine effect using the Weighted Average of Adequately Powered (WAAP) estimator (Ioannidis et al., 2017; Stanley et al., 2017). The WAAP is a weighted average that uses optimal weights ($1/SE_{ij}^2$) on the only 'adequately powered' estimates, which are usually defined as having standard errors smaller than the multilevel mixed-effects model estimates divided by 2.8 (Stanley et al., 2017).

4.2 Results

Table 2 reports the associated results for the whole sample of 2,464 estimates (*Panel A*) and our baseline sample of 1,397 estimates (*Panel B*). Columns [1] and [2] present results for type II bias, using respectively the adjusted and the absolute t-statistics. Columns [3] to [7] depict results for type I bias considering continuous t-statistics for each type of shock (i.e., each meta-regression subgroup).

For both *Panel A* and *Panel B*, the intercepts (FAT) in columns [1] and [2] are positive[10] and highly significant, pointing to the existence of type II publication selection bias. This suggests that researchers have incentives to promote results with higher statistical significance, in line with most MRA findings (Doucouliagos and Stanley, 2013).

[10] The sign of the intercept is only meaningful for the absolute measure of the t-Student, its absolute value being necessarily positive.

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Table 2: Publication Selection Bias and Genuine Effect Tests [Baseline Results]

	[1]	[2]	[3]	[4]	[5]
	All local shocks		**Main channels of transmission**		
	Absolute t-student	Adjusted t-student	Agr. shock (+)	Agr. shock (-)	Hydr./Min. shock (+)
Panel A: whole sample					
[i] FAT-PET					
Mean beyond bias (PET)					
Precision (1/SE)	**-4.3E-04 ***	-9.0E-05	**-0.003 *****	-0.001	-2.8E-04
	(0.000)	(0.000)	**(0.001)**	(0.001)	(0.001)
Publication bias (FAT)					
Constant	**2.383 *****	**1.359 *****	-0.329	**1.469 *****	0.566
	(0.119)	**(0.191)**	(0.411)	**(0.300)**	(0.460)
[ii] WAAP					
Mean beyond bias					
Constant	-	-	-	-	-
	-	-	-	-	-
#studies	64	64	24	35	14
Observations	2 464	2 464	710	1,049	543
%Observations	100%	100%	29%	43%	22%
Panel B: baseline coefficients only					
[i] FAT-PET					
Mean beyond bias (PET)					
Precision (1/SE)	-6.4E-05	4.9E-04	**-0.005 *****	-2.6E-04	0.001
	(0.000)	(0.000)	**(0.001)**	(0.001)	(0.001)
Publication bias (FAT)					
Constant	**2.492 *****	**1.864 *****	-0.214	**2.151 *****	0.708
	(0.126)	**(0.199)**	(0.452)	**(0.329)**	(0.601)
[ii] WAAP					
Mean beyond bias					
Constant	-	-	5.1E-05	**0.002 *****	0.001
	-	-	(0.001)	**(0.000)**	(0.000)
#studies	61	61	22	33	13
Observations	1 397	1 397	431	504	325
%Observations	100%	100%	31%	36%	23%

Notes: FAT-PET models are estimated with a multilevel mixed-effects model and the weighted average of the adequately powered (WAAP) is derived from Ioannidis et al. (2017) and Stanley et al. (2017). Panel A has 2,464 observations from 64 studies, while Panel B has 1,411 observations from 63 studies. The dependent variable is the t-statistic of the estimate of interest on conflicts. Standard errors are reported in parentheses and are adjusted for study- and channels of transmission-level clustering. Columns [1] and [2] report results for all local shocks, using the absolute value and adjusted t-statistic of the estimate of interest. Columns [3] to [5] focus on positive and negative agricultural shocks and positive hydrocarbon/mineral shocks for commodity exporters. Table A2 presents results for other shocks, including pure climatic shocks. For a detailed description of variables, see Table A3. $*p < 0.10, **p < 0.05, ***p < 0.01$. *Source: MRA database.*

To refine the assessment of publication bias (and derive the genuine risks of conflicts, if any), we then focus on our three main meta-regression subgroups: ***AS+***, ***AS-***, and ***HS+*** in columns [3] to [5] of Table 2 (the results for the other types of shocks are presented in the Appendix). The dependent variables are the t-statistics value of the collected estimate, as opposed to the adjusted and absolute value used when considering the whole sample. Results associated with these more homogeneous sets of estimates show a significant intercept in column [4] only. This suggests the presence of a type I publication selection bias in studies

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analyzing the effect of AS-. In other words, researchers tend to prefer studies in line with conventional views (Card and Krueger, 1995) when they study negative agricultural shocks, and in the present case, higher risks of conflicts. Our results also point to a rather "substantial" selectivity in that sub-literature, as supported by the FAT values.[11] Interestingly, as suggested by the funnel plots (see Online Appendix), we do not find any evidence of type I bias for studies focusing on AS+ (column [3]) and HS+ (column [5]). Since the majority of the estimates collected for AS+ and HS+ are price shocks (see table A1), these results are consistent with those of Blair et al. (2021), who find no evidence of publication selection bias in the literature on price shocks and conflicts. One potential but not definitive explanation is the nature of shocks: while AS+, and HS+ largely rely on market and price shocks, AS- largely rely on natural events (see table A1). It is possible that the analysis of climate events allows for a more arbitrary selection of results. Climate shocks can be captured by a range of variables (precipitation, drought, temperature, etc.) and parameters (different indicators, measures of variance over different periods, etc.). These methodological choices have theoretical implications and can lead authors into various empirical pitfalls (Auffhammer et al., 2013).[12] The results for other types of shocks (see Table A2) also point toward this explanation. Indeed, they suggest the presence of selection bias only in the regressions of pure positive and negative climate shocks, which are also measured with a heterogeneous set of climate variables (see Figure A1 and Table A1 in the Appendix). These elements will be discussed further in the heterogeneity analysis section.

When the adjusted and absolute t-statistics are used as dependent variable, it is hard to interpret the coefficients associated with $1/SE$ (precision parameter) as genuine effects, as the meta-group consists of a synthesis of studies that do not rest on a single transmission

[11] A FAT absolute value smaller than 1 is synonymous of "little to modest" selection bias, while a FAT test absolute value ranging between 1 and 2 rather signals "substantial" selectivity (Doucouliagos and Stanley, 2013).

[12] Additionally, the WAAP by Ioannidis et al. (2017) and Stanley et al. (2017) shows few adequately powered significant estimates for the subsample of baseline AS- estimates only. In other words, the greater variety of shocks associated with AS- is associated both with overall opportunities of (type I) publication selection bias *and* genuinely more unconditional risks of conflicts for the few subsample (150 out of 504 observations) of adequately powered estimates.

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channel. Columns [3] to [5] of Table 2 allow going beyond the publication bias and testing for the existence of genuine effects of income shocks on conflicts for each meta-subgroup. After filtering out the publication bias (slope coefficients reported in columns [3] and [5]), we find a negative effect of AS+ and no evidence of genuine effects for AS- and HS+. Put differently, after filtering out the publication bias, we find that only positive agricultural shocks genuinely influence (here, reduce) the risk of conflict. This does not mean that AS- and HS+ have no effect on conflicts, but that their effects depend on several factors that will be discussed in the heterogeneity analysis section.

To sum up, these results show that the literature on the effects of income shocks on conflicts suffers from two types of publication bias: researchers tend to prefer studies that (i) find higher risks of conflicts when they focus on AS- (type I bias); and (ii) generally promote results with higher statistical significance (type II bias). We also find evidence that AS+ are associated with lower risks of conflicts. In the next section, we look at how key interactive factors might affect the baseline results.

5 Heterogeneity Analysis

Individual studies on the link between income shocks and conflict vary greatly in terms of data and method used. The purpose of this section is to investigate whether authors' methodological choices systematically influence the estimated partial correlation coefficients and whether the estimated coefficients of publication bias from Section 4 survive the addition of moderator variables. More precisely, we examine if sections of the literature that focus specifically on pacifying or destabilizing shocks or use interaction models are affected differently by publication bias. In the Online Appendix, we also present the results of a Bayesian analysis (BMA) where we test whether systematic differences in the data and methodological choices made by the authors explain the variations in the results that they obtain.

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5.1 Publication Bias and Authors' Initial Assumptions on the Sign and Strength of the Mechanisms at Play

Figure 4 depicts the breakdown of our sample of selected regressions. It shows the authors' initial assumptions (i.e. ex-ante expectations) about the effect of the mechanism they are testing, and the interaction format they apply to test its robustness. We identify regressions testing a theoretically pacifying mechanism by selecting the ones where the authors analyze the effect of AS+ through any other mechanism than rapacity. Similarly, we identify regressions testing a theoretically stressful mechanism by selecting all regressions where the tested mechanism does not have a pacifying effect. Furthermore, we identify three categories of key interactive terms, namely ex-ante risk enhancers (i.e. assumed to increase the risk of conflict *ceteris paribus*), ex-ante risk absorbers (i.e. assumed to decrease the risk of conflict *ceteris paribus*), and interaction terms with no specific ex-ante expectations (undetermined moderator). A summary of the different key interactive terms and the rationale underpinning their introduction is presented in the Online Appendix.

Figure 4 indicates that a majority (68.9%) of the selected regressions test a stressful mechanism, 26% test a pacifying mechanism, and 5.1% test a mechanism with undetermined effects. This implies that most studies on income shocks and conflicts focus on the detrimental impact of income shocks, which limits the empirical evidence available on local income shocks as a way out of conflicts. The figure also reveals that 43.3% of the collected estimates (1,067 estimates) incorporate one or more unit-specific variables, indicating a recurring practice in empirical models of conflicts.[13] Interaction terms can help researchers identify the mechanisms at play by highlighting heterogeneous effects depending on the characteristics of the geographical areas studied. These moderator variables are model-specific and rarely similar across studies. As interaction models can help identify or mitigate the action of specific mechanisms, result searching bias is likely to be captured, if existent, in the choice of

[13]For example, in a study on weather shocks and peasant revolts in historical China, Jia (2014) interacts indicators of droughts and floods with sweet potatoes as food production (known to be more resilient to bad weather than rice or wheat production) as a "risk absorber" moderator.

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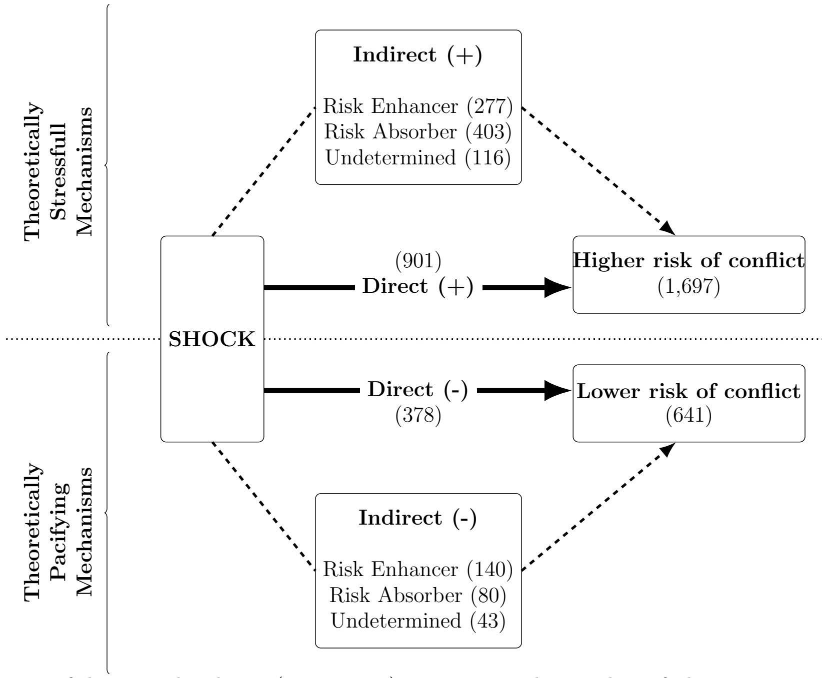
interacted variables.



Notes: Expected signs of direct and indirect (interaction) estimates. The number of observations concerned is given in parenthesis. 126 observations (not shown) refer to mechanisms with uncertain sign (including 118 direct estimates, 5 indirect estimates with a risk enhancer, 3 indirect estimates with a risk absorber). *Source: Authors compilation from MRA database.*

Figure 4: Expected Signs of Direct and Indirect Channels of Transmission

5.2 Method

To test if these methodological choices are a source of publication bias, we augment the baseline model with dummy variables indicating the type of mechanism or the type of interaction that is tested. When the multilevel random effect model includes covariates (or moderators) accounting for heterogeneity between studies, the model becomes best described as a "multilevel mixed-effect model". More specifically, Equations 2 and 3 become:

$$t_{ij} = \beta_0 + \beta_1 \frac{1}{SE_{ij}} + \beta_k \frac{x'_{ij}}{SE_{ij}} + \frac{\lambda_j}{SE_{ij}} + \varepsilon_{ij} \tag{4}$$

or

$$|t_{ij}| = \beta_0 + \beta_1 \frac{1}{SE_{ij}} + \beta_k \frac{x'_{ij}}{SE_{ij}} + \frac{\lambda_j}{SE_{ij}} + \varepsilon_{ij} \tag{5}$$

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where $x_{ij}^{'}$ stands for a set of variables capturing empirical study characteristics from the meta-sample that explain the differences in estimates between studies. β_0 measures the severity of publication bias conditional on the inclusion of controls, and β_1 is the mean β estimate corrected for publication bias but also conditional on the variables included.

Various multilevel random-effect methods have been proposed in the MRA literature to estimate the between-study variance in meta-regressions. The most commonly used method involves using a multilevel mixed-effect restricted maximum likelihood (REML) process, which assumes normal distributions for both the within and between-study effects. This method is preferred because it avoids downward-biased estimates of the between-study variance, underestimated standard errors, and anti-conservative inference.[14] We use the REML method to perform regressions on our extended sample of 2,464 observations (1,397 baseline estimates plus 1,067 interactive terms) to examine heterogeneity in the estimated effects of income shocks on conflicts due to interactions. To study heterogeneity due to the *ex-ante* direction of tested mechanisms by authors, we perform the regressions only on the baseline sample of 1,397 estimates to exclude potentially noisy effects of interactive terms in the analysis.

5.3 Results

Table 3 presents the empirical results for AS+, AS-, and HS+ when we control for the type of mechanism tested. We observe that negative and statistically significant coefficients are associated with pacifying mechanisms in Columns [2], [6], and [10], while positive and statistically significant coefficients are associated with stressful mechanisms in Columns [3], [7], and [11]. This implies that studies focusing on pacifying mechanisms report a lower risk of conflict following an income shock, while studies focusing on stressful mechanisms report a higher risk of conflict. In column [4], we also find that studies of positive agricultural shocks that do not present ex-ante-expectation on their tested mechanism report a higher risk of conflict. Our findings indicate that publication bias is conditional on the type of

[14] Anti-conservative inference happens when scholars and researchers do not update their prior and beliefs when they face incomplete information, noise, fallible data or counter-intuitive results for instance.

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mechanism tested. Specifically, a positive and statistically significant intercept is found when we control for pacifying mechanisms in columns [2], [6], and [10]. When we control for stressful mechanisms, the intercept in column [11] is also statistically significant (at the 0.10 level) but negative. These results suggest that there is a type I publication selection bias in studies that do not focus on pacifying mechanisms and in studies encompassing HS+ that do not test stressful mechanisms. In summary, the results suggest that the current literature tends to favor the publication of results that show (i) the detrimental impacts of income shocks on the local risk of conflict through theoretically stressful/undefined mechanisms, and (ii) that pacifying mechanisms in the extractive sector reduce the local risk of conflict.

Table 3: Explaining Heterogeneity in the Estimated Effects of Income Shocks on Conflicts [Direction of the Tested Mechanism]

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Main channels of transmission											
	AS+				AS-				HS+			
Whole sample												
Precision (1/SE)	**-0.005 *****	**-0.005 *****	**-0.005 *****	**-0.005 *****	-2.6E-04	-3.8E-04	-3.2E-04	-2.6E-04	0.001	0.001	0.001	0.001
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.214	**1.581 *****	-0.532	-0.388	**2.151 *****	**2.446 *****	0.535	**2.154 *****	0.708	**1.242 ****	**-2.108 ***	0.708
	(0.452)	**(0.434)**	(0.391)	(0.437)	**(0.329)**	**(0.278)**	(0.761)	**(0.337)**	(0.601)	**(0.556)**	**(1.237)**	(0.601)
Type of mechanism												
Mecha. pacifying=1		**-2.253 *****				**-4.849 *****				**-3.350 *****		
		(0.325)				**(1.130)**				**(1.353)**		
Mecha. stressful=1			**2.111 *****				**1.834 *****				**3.350 ****	
			(0.335)				**(0.788)**				**(1.353)**	
Mecha. undefined=1				**3.827 ****				-0.057				-
				(1.931)				(1.004)				-
#studies	22	22	22	22	33	33	33	33	13	13	13	13
Observations	431	431	431	431	504	504	504	504	325	325	325	325
%Observations	31%	31%	31%	31%	36%	36%	36%	36%	23%	23%	23%	23%

Notes: Models are estimated using a multilevel mixed-effects model on the baseline sample of 1,397 observations and 61 studies. The dependent variable is the t-statistic of the estimate of interest on conflicts. Standard errors are reported in parentheses and are adjusted for study level clustering. Columns [1]-[4] analyze positive agricultural shocks, columns [5]-[8] analyze negative agricultural shocks, and columns [9]-[12] analyze positive hydrocarbon/mineral shocks. Results on other shocks – including pure climatic shocks – are presented in Table A2 in the Appendices. A detailed description of all variables can be found in Table A3, while the detailed composition of mechanisms is available in the Online Appendix. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. *Source: Authors' compilation from MRA database*

Table 4 shows results when controlling for the type of interactive term in the regression. Coefficients associated with a risk absorber interaction term are negative and statistically significant in Columns [2], [6], and [10]. Conversely, coefficients associated with a risk enhancer interaction term are positive and statistically significant in Columns [3], [7], and [11]. This indicates that studies using interactions report a higher (or lower) local risk of conflict in line with their expectations. Additionally, we find that studies focusing on AS+ tend

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to prefer a result for the intercept that shows a lower risk of conflict when they include an interaction with a risk enhancer, while studies focusing on HS+ and AS- tend to prefer an intercept showing a higher risk of conflict when there is an interaction with a risk absorber. This indicates a small or modest type I publication selection bias, implying a tendency to select interaction terms of opposite direction as long as they support the tested mechanism.

Table 4: Explaining Heterogeneity in the Estimated Effects of Income Shocks on Conflicts [Inclusion of Interactions]

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Main channels of transmission											
	AS+				AS-				HS+			
Whole sample												
Precision (1/SE)	**-0.003 *****	**-0.003 ****	**-0.002 ****	**-0.003 *****	-0.001	3.7E-04	-0.001	-0.001	-3.0E-04	2.0E-04	-3.1E-04	-1.0E-04
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.329	-0.204	**-0.761 ***	-0.338	**1.469 *****	**2.021 *****	**1.146 *****	**1.479 *****	0.566	**0.899 ***	0.287	0.549
	(0.411)	(0.413)	**(0.396)**	(0.412)	**(0.300)**	**(0.271)**	**(0.321)**	**(0.298)**	(0.460)	**(0.474)**	(0.467)	(0.461)
Type of interaction												
Risk absorber=1		**-1.991 *****				**-3.379 *****				**-2.726 *****		
		(0.286)				**(0.110)**				**(0.235)**		
Risk enhancer=1			**3.389 *****				**1.321 *****				**2.385 *****	
			(0.174)				**(0.169)**				**(0.287)**	
Risks uncertain=1				0.528				-0.331				-0.298
				(0.363)				(0.360)				(0.304)
#studies	24	24	24	24	35	35	35	35	14	14	14	14
Observations	710	710	710	710	1,049	1,049	1,049	1,049	543	543	543	543
%Observations	29%	29%	29%	29%	43%	43%	43%	43%	22%	22%	22%	22%

Models are estimated using a multilevel mixed-effects model on the baseline sample of 1,397 observations and 61 studies. The dependent variable is the t-statistic of the estimate of interest on conflicts. Standard errors are reported in parentheses and are adjusted for study level clustering. Columns [1]-[4] analyze positive agricultural shocks, columns [5]-[8] analyze negative agricultural shocks, and columns [9]-[12] analyze positive hydrocarbon/mineral shocks. Results on other shocks – including pure climatic shocks – are presented in Table A2 in the Appendices. A detailed description of all variables can be found in Table A3, while the detailed composition of risk absorbers, risk enhancers and risk uncertain is available in the Online Appendix. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. *Source: Authors' compilation from MRA database.*

6 Discussion and Conclusion

Do income shocks locally affect the probability of internal conflicts? This paper uses meta-regression analysis (MRA) to review the recent empirical literature on local income shocks and conflicts in developing countries. Using a sample of 2,464 point estimates from 64 studies, we evaluate the presence of publication selection bias and discuss the relevance of a range of methodological limitations and advances reported in previous reviews of the conflict literature. Thanks to the MRA, we can identify and accommodate publication selection bias,which arises when researchers, editors or reviewers choose to report or publish empirical estimates that conform to their expectations (type I publication selection bias) or that are

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statistically significant (type II publication selection bias).

We find no evidence of an average and unconditional genuine effect of income-related shocks on the risk of conflict at the infra-national scale. Therefore, the effect of climate changes, commodity price fluctuations and natural resources endowment on the risk of conflict does not seem to systematically transit through variations in local incomes and economic prospects. Nonetheless, the fluctuation of local incomes may affect the risk of conflict under certain conditions. To account for heterogeneity in the authors' narratives, we divide the meta-sample into coherent sets based on the type (agricultural, extractive, or other) and direction (wealth-increasing or -decreasing) of the shock. On average, we find a reducing and statistically significant effect of wealth-increasing shock in the agriculture sector on the risk of conflict, but no statistically significant effects of wealth-decreasing shocks or shocks in the extractive sector. Moreover, we find that the literature suffers substantially from two types of publication selection bias: it favors the publication of results with higher statistical significance (type II bias), and showing the detrimental effects of income shocks (type I bias). Studies of negative agricultural shocks (droughts, floods) are particularly affected by the latter type of bias, probably because 98.7% of the estimates in this subgroup test theoretically stressful mechanisms. We also suspect the influence of result searching bias in the choice of climate-related variables, since we find that overestimation is more likely for studies focusing on climate shocks. Indeed, climatic variables are intricate (Auffhammer et al., 2013) and recent micro-evidence suggests that their effect on local poverty is heterogeneous (Azzarri and Signorelli, 2020).

This MRA complements the existing body of meta-analysis on the economic origins of conflict in developing countries. O'Brochta (2019) finds no aggregate relationship between conflicts and natural resources, and Blair et al. (2021) obtain similar conclusions for commodity prices. Our results complement theirs by showing that there is no aggregated effect of income shocks on the risk of conflict at the infra-national scale. Vesco et al. (2020) find

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that both extractive resource wealth and renewable resource scarcity (e.g., forest, water, vegetation) increase the risk of conflict. When decomposing for the nature of main income shocks (AS+, AS-, HS+), our results suggest that wealth-increasing and -decreasing shocks do not have a symmetric effect on conflict, backing supporters of non-wealth-related factors (including grievances and state capacity) as motives of conflicts (de Mesquita, 1985; Cramer, 2002; Michalopoulos and Papaioannou, 2020). Hsiang et al. (2013, 2014) find that deviations from normal precipitation and mild temperatures systematically increase the risk of conflict. In line with their conclusions and several scholars (Theisen et al., 2012; Sarsons, 2015), our results suggest that the effect of climatic events is unlikely to be operating solely through changes in local agricultural income. Finally, our results show that researchers' expectations on the theoretical mechanisms at play (above all, opportunity cost and rapacity) distort statistical inference and the resulting understanding of research on the local causes of conflict. Overall, this MRA advocates for caution in generalizing the results of conflict studies, especially for recommending policies to countries outside the study area. The genuine effect of positive agricultural shocks and the asymmetries we find in the literature call for more analysis of the peacemaking mechanisms linking income shocks to local risk of conflict.

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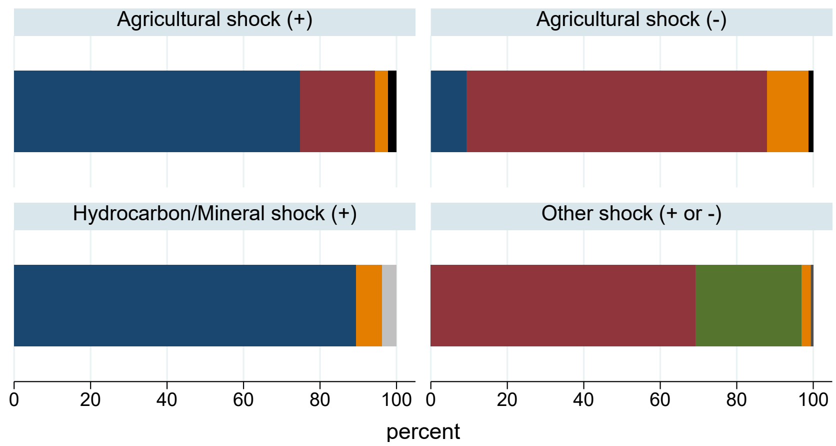
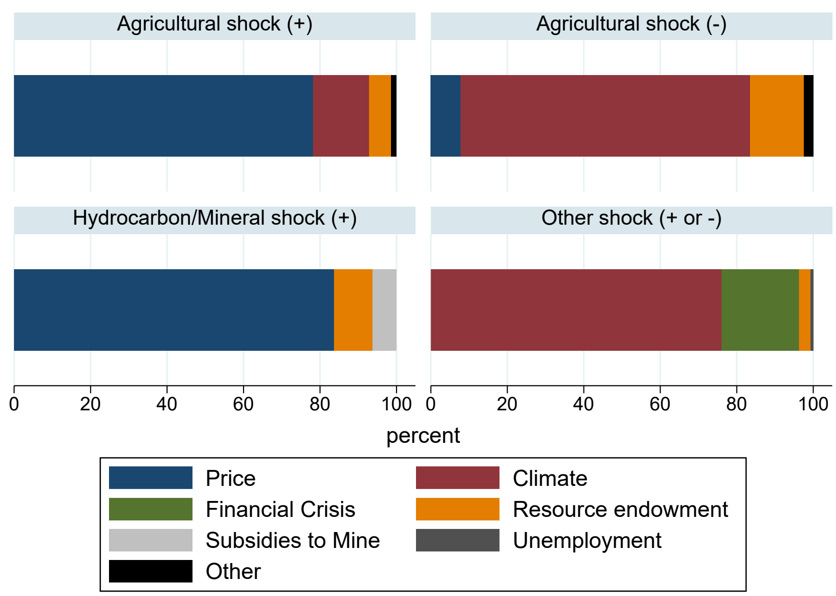
Appendices

(a) Total (2,464)



(b) Baseline (1,397)



Notes: Categories are not totally exclusive, so percentages do not necessarily sum to 100 for each meta-subgroup. For example, estimates that instrument an output measure with a climate variable will be classified both as climate and production shocks. The shares of each subgroup and their components are detailed in Table A1. *Source: Authors' compilation from MRA database.*

Figure A1: Channels of Transmission [Share of Estimates in Meta-Subgroups]

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Table A1: Channels of Transmission [Share of Estimates for Each Category of Shock in Each Meta-Subgroup]

	Total				Baseline			
	AS+ (%)	AS- (%)	HS+ (%)	Other (%)	AS+ (%)	AS- (%)	HS+ (%)	Other (%)
Price shocks	**74.8**	**9.7**	**89.5**	**0.0**	**78.2**	**8.1**	**83.7**	**0.0**
Incl. production*prices	72.7	5.5	13.4	0.0	75.6	1.8	20.6	0.0
Incl. location*prices	0.0	0.0	68.9	0.0	0.0	0.0	60.3	0.0
Incl. consumption*prices	0.0	4.2	0.0	0.0	0.0	6.3	0.0	0.0
Incl. prices	2.1	0.0	0.0	0.0	2.6	0.0	0.0	0.0
Incl. rents	0.0	0.0	7.2	0.0	0.0	0.0	2.8	0.0
Climate shocks	**19.6**	**81.2**	**0.0**	**69.8**	**14.6**	**79.4**	**0.0**	**76.6**
Incl. precipitations	16.3	35.3	0.0	38.3	10.4	32.5	0.0	45.3
Incl. droughts	3.2	34.3	0.0	3.1	4.2	33.9	0.0	3.6
Incl. temperatures	0.6	4.7	0.0	27.2	0.9	6.9	0.0	26.3
Incl. floods	0.0	9.9	0.0	1.9	0.0	11.7	0.0	2.2
Ressource endowment shocks	**3.5**	**11.2**	**6.8**	**2.5**	**5.8**	**14.7**	**10.2**	**2.9**
Incl. water access	1.8	0.6	0.0	0.0	3.0	1.2	0.0	0.0
Incl. production/endowment	1.7	10.7	6.8	2.5	2.8	13.5	10.2	2.9
Other shocks	**2.1**	**1.2**	**3.7**	**28.4**	**1.4**	**2.6**	**6.2**	**21.2**
Incl. financial crisis	0.0	0.0	0.0	27.8	0.0	0.0	0.0	20.4
Incl. subsidies to Mine	0.0	0.0	3.7	0.0	0.0	0.0	6.2	0.0
Incl. unemployment	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.7
Incl. other	2.1	1.2	0.0	0.0	1.4	2.6	0.0	0.0
Observations	710	1,049	543	162	431	504	325	137

Notes: Categories are not totally exclusive, so percentages do not necessarily sum to 100 for each meta-subgroup. For example, estimates that instrument an output measure with a climate variable will be classified both as climate and production shocks. AS+: positive agricultural shock. AS-: negative agricultural shock. HS+: positive hydrocarbon and mineral shock. *Source: Authors' compilation from MRA database.*

Table A2: Table of Results [Other Shocks]

	Pure climatic shock (+)		Pure climatic shock (-)		Other potential detrimental shocks	
	Precision (1/SE)	Constant	Precision (1/SE)	Constant	Precision (1/SE)	Constant
Baseline regression	0.006	**-2.387***	-0.001	**2.563 *****	-0.002	1.262
Non-lineartities						
Control for risk absorber=1	0.006	**-2.318 *****	-0.001	**2.563 *****	0.001	**1.577 ****
Control for risk enhancer=1	0.006	**-2.416 *****	0.000	**2.465 *****	-0.002	1.262
Control for risk uncertain=1	0.006	**-2.387***	-0.001	**2.563 *****	-0.002	1.262
Baseline regression	0.004	**-2.130 *****	0.000	**2.414 *****	-0.001	**1.726 *****
Mechanisms						
Mecha. pacifying=1	0.004	**-2.130 *****	0.000	**2.414 *****	-0.001	**1.726 *****
Mecha. stressful=1	0.004	**-2.130 *****	0.000	**2.414 *****	-0.001	**1.726 *****
Mecha. undefined=1	0.004	**-2.130 *****	0.000	**2.414 *****	-0.001	**1.726 *****
# Studies	5		8		3	
# Observations	35		77		50	
% Observations	1.4%		3.1%		2.0%	

Notes: All models are estimated with a multilevel mixed-effects model. The dependent variable is the t-statistic of the estimate of interest on conflicts as dependent variable. Standard errors (adjusted for study level clustering) are not reported to save space. The table reports the mean beyond bias (Precision (1/SE)) and the publication bias (Constant) for each specification A detailed description of all variables is available in Table A3. The detailed composition of mechanisms, risk absorbers, risk enhancers and risk uncertain is available in the Online Appendix. The detailed composition of mechanisms is available in Table xx. $*p < 0.10, **p < 0.05, ***p < 0.01$. *Source: Authors' compilation from MRA database.*

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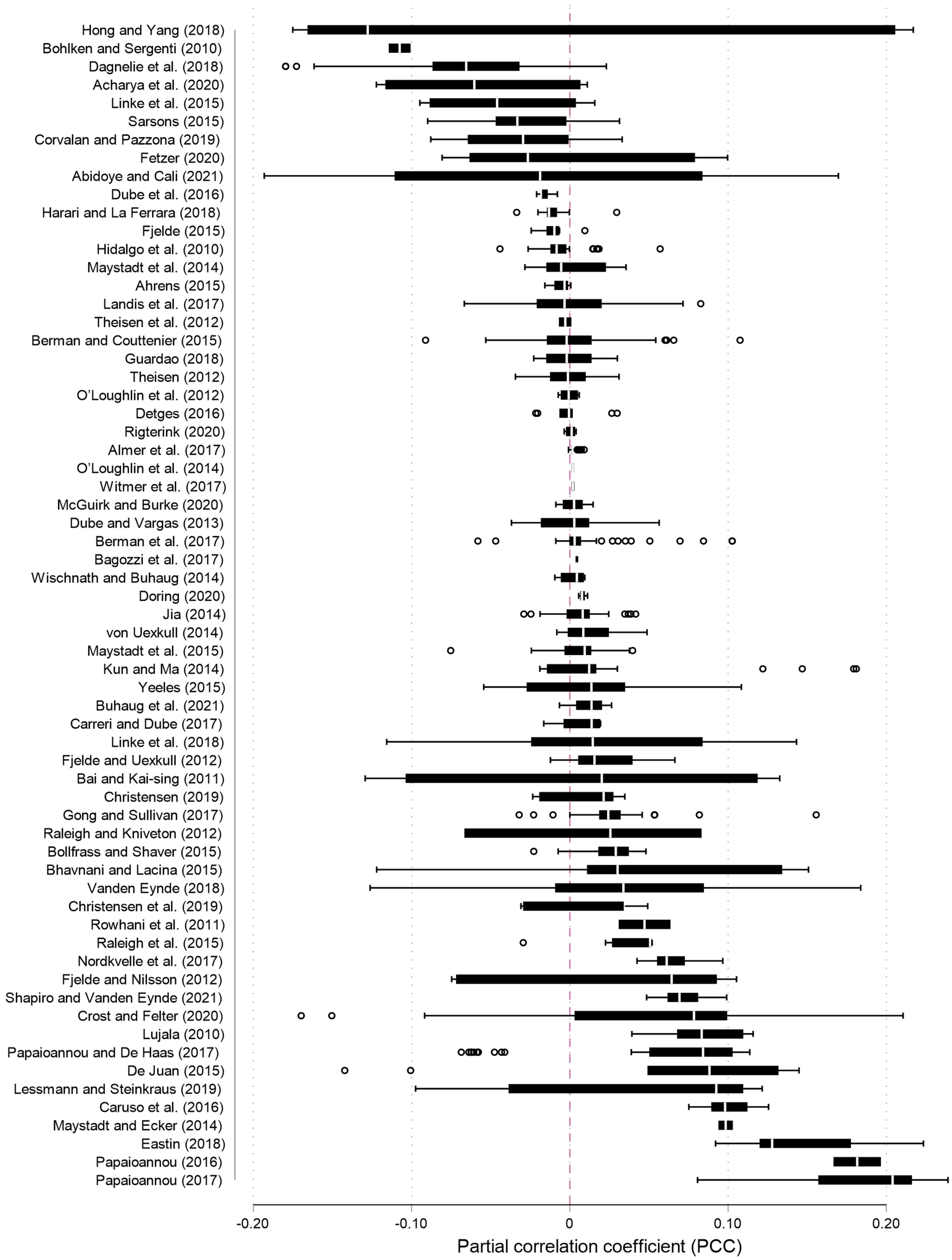

Notes: Dots denote outliers. Most PCC values fall between -0.1 and 0.1, implying that income shocks may have a small impact on the risk of conflict locally. *Source: Authors' compilation from MRA database.*

Figure A2: The Box Plot of PCCs within Studies.

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Table A3: Meta-Regression Variables Definition and Descriptive Statistics

Variable name	Variable description	(N= 2,464) Mean	S.D.
t-student	Student's t-test of estimates between income shocks and conflicts	0.561	2.612
Absolute t-student	Absolute value of t-student	2.324	1.317
Adjusted t-student	Adjusted t-student (reversed sign for Pos. Agr. Shocks)	1.052	2.456
Partial	Partial correlation of estimates between income shocks and conflicts	0.010	0.056
Precision	1/Standard error of the partial correlation	219.292	245.048
Transmission channels			
Pos. agr. shocks*	BV = 1: income shock is a positive agricultural shock	0.288	0.453
Neg. agr. shocks	BV = 1: income shock is a negative agricultural shock	0.426	0.495
Pos. hydr./min. shocks	BV = 1: income shock is a positive hydrocarbon or mineral shock	0.220	0.415
Other shocks	BV = 1: other income shock (e.g., financial shock, drug shock)	0.066	0.248
Mechanisms and interactive models			
Mecha. uncertain*	BV = 1: if mechanism is uncertain	0.051	0.220
Mecha. peace*	BV = 1: if pacifying mechanism encompassed	0.260	0.439
Mecha. stress	BV = 1: if stressfull mechanism encompassed	0.689	0.463
Risk uncertain*	BV = 1: if interactive term with no clear ex-ante effect	0.065	0.246
Risk absorber*	BV = 1: if interactive term is theoretically an abridgment for conflict	0.197	0.398
Risk enhancer	BV = 1: if interactive term is theoretically an amplifier for conflict	0.171	0.377
Publication outlet			
No top 5*	BV = 1: the paper is not in top 5 Economics or Political science journal	0.827	0.378
Top 5	BV = 1: the paper is in top 5 Economics or Political science journal	0.173	0.378
No conflict review*	BV = 1: the paper is not in conflict specialized journal	0.929	0.256
Conflict review	BV = 1: the paper is published in a conflict specialized journal	0.071	0.256
Core results*	BV = 1: estimates taken from the core paper	0.761	0.427
Result from appendix	BV = 1: estimates taken from appendix	0.239	0.427
Age of study	Age of study, in year, in 2023	6.726	2.507
SJR score	SCImago Journal score of the paper (the year of publication)	5.632	4.488
Geography			
No country focus*	BV = 1: estimates is not focusing on a given country	0.500	0.500
Country focus	BV = 1: estimates focus on a given country	0.500	0.500
Worldwide*	BV = 1: focus on two or several regions	0.066	0.248
Africa	BV = 1: focus on Africa as a whole or Sub-Saharan Africa (SSA)	0.551	0.497
EAP	BV = 1: focus on East Asia Pacific (World Bank Group definition)	0.198	0.399
LAC	BV = 1: focus on Latin America and the Caribbean (WBG def.)	0.111	0.314
South Asia	BV = 1: focus on Souht Asia (WBG def.)	0.074	0.262
Model characteristics			
No MLE*	BV = 1: if linear estimator used (e.g., GLM, OLS)	0.778	0.415
Maximum-likelihood est.	BV = 1: if maximum-likelihood estimator used (e.g., Logit, PPML)	0.222	0.415
No specific effects*	BV = 1: if no specific effect used	0.072	0.259
Specific effects	BV = 1: if fixed, mixed or random effects used	0.928	0.259
No cluster unit reference*	BV = 1: if no clustering on the unit of reference	0.531	0.499
Cluster unit reference	BV = 1: if estimates clustered on the unit of reference	0.469	0.499
Pre Cold War end*	BV = 1: if pre Cold War end (until 1991)	0.535	0.499
Post Cold War end	BV = 1: if post Cold War end (after 1991)	0.465	0.499
No small grids*	BV = 1: if no small grids	0.603	0.489
Small grids	BV = 1: if small grids ($\leq 0.5° * 0.5°$) are used to capture conflicts	0.397	0.489
Sample size	Natural logarithm of sample size	9.594	2.274

Notes: BV means binary variable, with a value of 1 if condition is fulfilled and zero otherwise. DV: dependent variable. *: used as reference category in BMA. #: 92 observations out of 2,464 use a mix of price and climatic shocks. *Source: Authors' compilation from MRA database.*

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Table A3 continued: Meta-Regression Variables Definition and Descriptive Statistics

Variable name	Variable description	(N= 2,464) Mean	S.D.
Conflict characteristics			
Usual conflict data*	BV = 1: if usual conflict data used (i.e., ACLED, UCDP, UCDP/PRIO)	0.459	0.498
Unusual conflict data	BV = 1: if non-usual conflict data used	0.541	0.498
Conflict incidence*	BV = 1: if DV is conflict incidence	0.903	0.296
Conflict duration	BV = 1: if DV is conflict duration	0.028	0.164
Conflict onset	BV = 1: if DV is conflict onset	0.069	0.254
No local conflict*	BV = 1: if DV is not a local conflict (above Admin2 level or at large grids level)	0.181	0.385
Conflict local	BV = 1: if DV is a local conflict (below Admin1 level or at small grids level)	0.819	0.385
Non lethal*	BV = 1: if DV is not a lethal conflict	0.235	0.424
Lethal	BV = 1: if DV is a lethal conflict by definition	0.765	0.424
Other conflict*	BV = 1: if DV refers to other/undefined type of conflicts	0.337	0.473
Armed conflicts	BV = 1: if DV refers to armed conflicts and battles	0.278	0.448
Crimes	BV = 1: if DV refers to crimes	0.126	0.332
Social unrests	BV = 1: if DV refers to social unrest	0.235	0.424
Violence against citizens	BV = 1: if DV refers to violence against citizens	0.024	0.153
Measures of shocks			
No quasi experimental*	BV = 1: if not endowment*shock used	0.496	0.500
Quasi experimental	BV = 1: if endowment*shock used	0.504	0.500
No labor intensive*	BV =1: if shock not based on labor intensive resource	0.665	0.472
Labor intensive resources	BV =1: if shock based on labor intensive resource	0.335	0.472
Others*	BV =1: if shock refers to other type of shocks	0.165	0.371
Climatic shock#	BV =1: if climatic shock used	0.507	0.500
Price shock#	BV =1: if price shock used	0.365	0.481
Model specification			
No past conflict*	BV = 1: if the estimate doesn't control for past conflicts	0.892	0.310
Control for past conflicts	BV = 1: if the estimate controls for past conflicts	0.108	0.310
No spatial factor*	BV = 1: if the estimate doesn't control for neighboring conflict	0.916	0.277
Control conflict spatial	BV = 1: if the estimate controls for neighboring conflict	0.084	0.277
No population*	BV = 1: if the estimate doesn't control for population density/pop. size	0.691	0.462
Control population	BV = 1: if the estimate controls for population density/pop. size	0.309	0.462
No GDP*	BV = 1: if the estimate doesn't control for GDP	0.876	0.329
Control GDP	BV = 1: if the estimate controls for GDP or equivalent	0.124	0.329

Notes: BV means binary variable, with a value of 1 if condition is fulfilled and zero otherwise. DV: dependent variable. *: used as reference category in BMA. #: 92 observations out of 2,464 use a mix of price and climatic shocks. *Source: Authors' compilation from MRA database.*

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Table A4: Characteristics of Individual Studies

#	Study	Title	Review	SJR score	Regressions #	Regressions % total	Interaction #	Interaction %	Subgroup	Mechanism(s)	Time period(s)	Region	Country focus
1	Abidoye and Cali (2021)	Income Shocks and Conflict: Evidence from Nigeria	Journal of African Economies	0.520	22	0.9%	0	0.0%	AS+; AS-	Pacifying; stressful	2004-2011	SSA	Nigeria
2	Acharya et al. (2020)	Security in the Absence of a State: Traditional Authority, Livestock Trading, and Maritime Piracy in Northern Somalia	Journal of Theoretical Politics	0.954	10	0.4%	10	0.9%	AS+	Pacifying	2000-2012	SSA	Somalia (Somaliland, Puntland)
3	Ahrens (2015)	Civil Conflicts, Economic Shocks and Night-time Lights	Peace Economics, Peace Science and Public Policy#	0.186	4	0.2%	0	0.0%	AS+	Pacifying	1992-2010	SSA	No
4	Almer et al. (2017)	Water Scarcity and Rioting: Disaggregated Evidence from Sub-Saharan Africa	Journal of Environmental Economics and Management	2.198	162	6.6%	84	7.9%	AS-	Stressful	1990-2011	SSA	No
5	Bagozzi et al. (2017)	Droughts, Land Appropriation, and Rebel Violence in the Developing World	The Journal of Politics	4.220	4	0.2%	0	0.0%	AS-	Stressful	1995-2008	World	No
6	Bai and Kai-sing (2011)	Climate Shocks and Sino-nomadic Conflict	The Review of Economics and Statistics	6.765	26	1.1%	0	0.0%	AS+; AS-	Pacifying; stressful	-220-1839	EAP	China
7	Berman and Couttenier (2015)	External Shocks, Internal Shots: The Geography of Civil Conflicts	The Review of Economics and Statistics	5.133	246	10.0%	120	11.2%	AS+; other	Pacifying; stressful	1989-2005; 1989-2006; 1997-2006	SSA	No
8	Berman et al. (2017)	This Mine is Mine! How Minerals Fuel Conflicts in Africa	American Economic Review°	12.047	227	9.2%	130	12.2%	HS+	Stressful	1997-2010	SSA	No
9	Bhavnani and Lacina (2015)	The Effects of Weather-Induced Migration on Sons of the Soil Riots in India	World Politics	3.646	5	0.2%	4	0.4%	AS-	Stressful	1982-2000	South Asia	India
10	Bohlken and Sergenti (2010)	Economic Growth and Ethnic Violence: an Empirical Investigation of Hindu—Muslim Riots in India	Journal of Peace Research#	2.272	2	0.1%	0	0.0%	AS+	Pacifying	1982-1995	South Asia	India
11	Bollfrass and Shaver (2015)	The Effects of Temperature on Political Violence: Global Evidence at the Subnational Level	PLoS ONE	1.427	30	1.2%	0	0.0%	AS+; AS-; CS+; CS-	Uncertain	1989-2008	World	No
12	Buhaug et al. (2021)	A Conditional Model of Local Income Shock and Civil Conflict	The Journal of Politics	3.027	15	0.6%	12	1.1%	AS-	Stressful	1971-2013	World	No
13	Carreri and Dube (2017)	Do Natural Resources Influence Who Comes to Power, and How?	The Journal of Politics	4.220	4	0.2%	0	0.0%	HS+	Stressful	1997-2005	LAC	Colombia
14	Caruso et al. (2016)	Climate Change, Rice Crops, and Violence: Evidence from Indonesia	Journal of Peace Research#	3.586	20	0.8%	0	0.0%	AS-	Stressful	1993-2003	EAP	Indonesia
15	Christensen (2019)	Concession Stands: How Mining Investments Incite Protest in Africa	International Organization	7.363	21	0.9%	14	1.3%	HS+	Stressful	1997-2013	Africa	No
16	Christensen et al. (2019)	Strategic Violence during Democratization: Evidence from Myanmar	World Politics	2.861	5	0.2%	2	0.2%	HS+	Stressful	2006-2010; 2006-2015; 2011-2015	EAP	Myanmar
17	Corvalan and Pazzona (2019)	Persistent Commodity Shocks and Transitory Crime Effects	Journal of Economic Behavior and Organization	1.482	34	1.4%	0	0.0%	HS+	Pacifying	2003-2008; 2003-2013	LAC	Chile
18	Crost and Felter (2020)	Export Crops and Civil Conflict	Journal of the European Economic Association	7.792	118	4.8%	46	4.3%	AS+	Pacifying; stressful	2001-2009; 2003-2009	EAP	Philippines
19	Dagnelie et al. (2018)	Violence, Selection and Infant Mortality in Congo	Journal of Health Economics	3.106	80	3.2%	0	0.0%	HS+	Stressful	1997-2004	SSA	Congo, Dem. Rep.
20	De Juan (2015)	Long-Term Environmental Change and Geographical Patterns of Violence in Darfur, 2003–2005	Political Geography	2.025	10	0.4%	0	0.0%	AS+; AS-	Pacifying; stressful	2003-2005	SSA	Southern Sudan (Darfur)
21	Detges (2016)	Local Conditions of Drought-Related Violence in Sub-Saharan Africa: the Role of Road and Water Infrastructures	Journal of Peace Research#	3.586	10	0.4%	8	0.7%	AS-	Stressful	1990-2010	SSA	No
22	Doring (2020)	Come Rain, or come Wells: How Access to Groundwater Affects Communal Violence	Political Geography	1.527	6	0.2%	0	0.0%	AS-	Stressful	1990-2014	World; SSA	No
23	Dube and Vargas (2013)	Commodity Price Shocks and Civil Conflict: Evidence from Colombia	Review of Economic Studies°	12.200	55	2.2%	6	0.6%	AS+; HS+	Pacifying; stressful	1988-2004; 1988-2005	LAC	Colombia
24	Dube et al. (2016)	From Maize to Haze: Agricultural Shocks and the Growth of the Mexican Drug Sector	Journal of the European Economic Association	8.113	54	2.2%	0	0.0%	AS+	Pacifying	1990-2005; 1990-2010	LAC	Mexico
25	Eastin (2018)	Hell and High Water: Precipitation Shocks and Conflict Violence in the Philippines	Political Geography	1.659	12	0.5%	0	0.0%	AS-	Stressful	2001-2007	EAP	Philippines
26	Fetzer (2020)	Can Workfare Programs Moderate Conflict? Evidence from India	Journal of the European Economic Association	7.792	43	1.7%	22	2.1%	AS+ ;AS-	Pacifying; stressful	2000-2010; 2000-2014	South Asia	India
27	Fjelde (2015)	Farming or Fighting? Agricultural Price Shocks and Civil War in Africa	World Development	2.253	12	0.5%	0	0.0%	AS+; AS-	Pacifying; stressful	1990-2010	Africa	No
28	Fjelde and Nilsson (2012)	Rebels against Rebels: Explaining Violence between Rebel Groups	Journal of Conflict Resolution#	3.448	12	0.5%	0	0.0%	HS+; other	Stressful	1987-2007	World	No
29	Fjelde and Uexkull (2012)	Climate triggers: Rainfall anomalies, vulnerability and communal conflict in Sub-Saharan Africa	Political Geography	2.137	15	0.6%	5	0.5%	AS+; AS-	Pacifying; stressful	1990-2008	SSA	No
30	Gong and Sullivan (2017)	Conflict and Coffee: Are Higher Coffee Prices Fuelling Rebellion in Uganda?	Journal of African Economies	0.533	47	1.9%	0	0.0%	AS+; AS-	Pacifying; stressful	2002-2014	SSA	Uganda
31	Guardao (2018)	Land Tenure, Price Shocks, and Insurgency: Evidence from Peru and Colombia	World Development	2.254	54	2.2%	49	4.6%	AS-	Stressful	1980-2000; 1988-2005	LAC	Colombia; Peru
32	Harari and La Ferrara (2018)	Conflict, Climate, and Cells: A Disaggregated Analysis	The Review of Economics and Statistics	8.363	19	0.8%	5	0.5%	AS+	Pacifying	1997-2011	SSA	No
33	Hidalgo et al. (2010)	Economic Determinants of Land Invasions	The Review of Economics and Statistics	7.882	73	3.0%	56	5.2%	AS-; other	Stressful	1988-2004; 1991; 2000	LAC	Brazil
34	Hong and Yang (2018)	Oilfields, Mosques and Violence: Is There a Resource Curse in Xinjiang?	British Journal of Political Science°	4.116	48	1.9%	30	2.8%	HS+	Pacifying	1998-2005	EAP	China (Xinjiang)

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Table A4 continued: Characteristics of Individual Studies

#	Study	Title	Review	SJR score	Regressions #	Regressions % total	Interaction #	Interaction %	Channel(s)	Mechanism(s)	Time period(s)	Region	Country focus
35	Jia (2014)	Weather Shocks, Sweet Potatoes and Peasant Revolts in Historical China	The Economic Journal	5.264	182	7.4%	92	8.6%	AS-	Stressful	1470-1900	EAP	China
36	Kung and Ma (2014)	Can Cultural Norms Reduce Conflicts? Confucianism and Peasant Rebellions in Qing China	Journal of Development Economics	4.712	77	3.1%	32	3.0%	AS-	Stressful	1651-1910	EAP	China (Shandong)
37	Landis et al. (2017)	Fording Differences? Conditions Mitigating Water Insecurity in the Niger River Basin	Political Geography	1.770	72	2.9%	72	6.7%	AS+; AS-	Pacifying; stressful	1997-2012	SSA	No
38	Lessmann and Steinkraus (2019)	The Geography of Natural Resources, Ethnic Inequality and Civil Conflicts	European Journal of Political Economy	1.107	9	0.4%	4	0.4%	HS+	Stressful	2000-2012	World	No
39	Linke et al. (2015)	Rainfall Variability and Violence in Rural Kenya: Investigating the Effects of Drought and the Role of Local Institutions with Survey Data	Global Environmental Change	3.504	10	0.4%	8	0.7%	AS+; AS-	Pacifying; stressful	2013	SSA	Kenya
40	Linke et al. (2018)	Drought, Local Institutional Contexts, and Support for Violence in Kenya	Journal of Conflict Resolution#	4.341	19	0.8%	16	1.5%	AS-	Stressful	2014	SSA	Kenya
41	Lujala (2010)	The Spoils of Nature: Armed Civil Conflict and Rebel Access to Natural Resources	Journal of Peace Research#	2.272	14	0.6%	0	0.0%	HS+	Stressful	1946-2001	World	No
42	Maystadt and Ecker (2014)	Extreme Weather and Civil War: Does Drought Fuel Conflict in Somalia through Livestock Price Shocks?	American Journal of Agricultural Economics	1.521	2	0.1%	0	0.0%	AS-	Stressful	1997-2009	SSA	Somalia
43	Maystadt et al. (2014)	Mineral Resources and Conflicts in DRC: a Case of Ecological Fallacy?	Oxford Economic Papers	0.687	20	0.8%	0	0.0%	HS+	Stressful	1997-2007	SSA	Congo, Dem. Rep.
44	Maystadt et al. (2015)	Local warming and violent conflict in North and South Sudan	Journal of Economic Geography	2.957	49	2.0%	22	2.1%	AS-; CS+; CS-	Uncertain; Stressful	1997-2009	SSA	Southern Sudan (incl. future South Sudan)
45	McGuirk and Burke (2020)	The Economic Origins of Conflict in Africa	Journal of Political Economy°	21.034	96	3.9%	53	5.0%	AS+; AS-	Pacifying; stressful	1989-2010; 1997-2013; 1999-2009	Africa	No
46	Nordkvelle et al. (2017)	Identifying the Effect of Climate Variability on Communal Conflict Through Randomization	Climatic Change	2.035	7	0.3%	0	0.0%	CS-	Uncertain	1989-2013	World	No
47	O'Loughlin et al. (2012)	Climate Variability and Conflict Risk in East Africa, 1990–2009	Proceedings of the National Academy of Sciences (PNAS)	6.868	10	0.4%	0	0.0%	AS+; AS-	Pacifying; stressful	1991-2009	SSA (East Africa)	No
48	O'Loughlin et al. (2014)	Effects of Temperature and Precipitation Variability on the Risk of Violence in Sub-Saharan Africa, 1980–2013	Proceedings of the National Academy of Sciences (PNAS)	6.898	2	0.1%	0	0.0%	CS-	Uncertain	1980-2012	SSA	No
49	Papaioannou (2016)	Climate Shocks and Conflict: Evidence from Colonial Nigeria	Political Geography	2.098	2	0.1%	0	0.0%	AS-	Stressful	1912-1945	SSA	Nigeria
50	Papaioannou (2017)	"Hunger Makes a Thief of Any Man": Poverty and Crime in British Colonial Asia	European Review of Economic History	0.702	33	1.3%	12	1.1%	AS-	Stressful	1910-1939	World	No
51	Papaioannou and De Haas (2017)	Weather Shocks and Agricultural Commercialization in Colonial Tropical Africa: Did Cash Crops Alleviate Social Distress?	World Development	2.122	93	3.8%	18	1.7%	AS-	Stressful	1920-1939	SSA	No
52	Raleigh and Kniveton (2012)	The Devil is in the Details: an Investigation of the Relationships between Conflict, Food Price and Climate across Africa	Journal of Peace Research#	2.985	16	0.6%	0	0.0%	CS+: CS-	Uncertain	1997-2009	SSA	No
53	Raleigh et al. (2015)	Come Rain or Shine: An Analysis of Conflict and Climate Variability in East Africa	Global Environmental Change	3.504	8	0.3%	0	0.0%	AS+; AS-	Pacifying; stressful	1997-2010	SSA (East Africa only)	No
54	Rigterink (2020)	Diamonds, Rebel's and Farmer's Best Friend: Impact of Variation in the Price of a Lootable, Labor-Intensive Natural Resource on the Intensity of Violent Conflict	Journal of Conflict Resolution#	2.671	32	1.3%	32	3.0%	HS+	Stressful	2004-2015	Africa	No
55	Rowhani et al. (2011)	Malnutrition and Conflict in East Africa: the Impacts of Resource Variability on Human Security	Climatic Change	1.532	2	0.1%	0	0.0%	AS+	Pacifying	2005-2010	SSA	No
56	Sarsons (2015)	Rainfall and Conflict: a Cautionary Tale	Journal of Development Economics	3.100	63	2.6%	35	3.3%	AS+	Pacifying	1970-1995	South Asia	India
57	Shapiro and Vanden Eynde (2023)*	Fiscal Incentives for Conflict: Evidence from India's Red Corridor	The Review of Economics and Statistics	8.245	6	0.2%	0	0.0%	HS+	Stressful	2007-2011	South Asia	India (Red corridor)
58	Theisen (2012)	Climate clashes? Weather variability, land pressure, and organized violence in Kenya, 1989–2004	Journal of Peace Research#	2.985	16	0.6%	0	0.0%	AS+; AS-	Pacifying; stressful	1989-2004	SSA	Kenya
59	Theisen et al. (2012)	Climate Wars? Assessing the Claim That Drought Breeds Conflict	International Security#	4.318	3	0.1%	2	0.2%	AS-	Stressful	1960-2004	Africa	No
60	Vanden Eynde (2018)	Targets of Violence: Evidence From India's Naxalite Conflict	Economic Journal	5.009	63	2.6%	54	5.1%	AS-	Stressful	2005-2011	South Asia	India
61	Wischnath and Buhaug (2014)	On Climate Variability and Civil War in Asia	Climatic Change	2.440	11	0.4%	0	0.0%	CS+; CS-	Uncertain	1951-2008	World	No
62	Witmer et al. (2017)	Subnational Violent Conflict Forecasts for Sub-Saharan Africa, 2015–65, Using Climate-sensitive Models	Journal of Peace Research#	3.888	2	0.1%	0	0.0%	CS-	Uncertain	1980-2012	SSA	No
63	Yeeles (2015)	Weathering Unrest: the Ecology of Urban Social Disturbances in Africa and Asia	Journal of Peace Research#	3.892	24	1.0%	0	0.0%	CS+; CS-	Uncertain	1960-2006	World	No
64	von Uexkull (2014)	Sustained Drought, Vulnerability and Civil Conflict in Sub-Saharan Africa	Political Geography	2.815	16	0.6%	12	1.1%	AS-	Stressful	1989-2008	SSA	No

Notes: *: published online in 2021 on peer-review journal website, but attributed to a journal issue in 2023. #: conflict specialized peer-review journal. °: top five peer-review journal in Economics or Political Science. SJR scores are established for the year of the publication. AS+: positive agricultural shock. AS-: negative agricultural shock. HS+: positive hydrocarbon shock. CS+ (CS-): positive (negative) pure climatic shock with no explicit impact through agriculture. Other: other potential detrimental shocks (positive drug shock; negative financial shock; negative labor market shock). EAP: East Asia & Pacific (World Bank definition). LAC: Latin America & the Caribbean (World Bank definition). SSA: Sub-Saharan Africa (World Bank definition). Except for Africa (Sub-Saharan Africa and North Africa), we consider a worldwide sample if two or more developing regions included in a given regression. The detailed description of transmission channels, mechanisms and interactive terms are presented in the Online Appendix. The full detailed references for these papers is available upon direct request *Source: Authors' compilation from MRA database.*

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Internal Conflicts and Shocks. A Narrative Meta-Analysis

ONLINE APPENDIX

March 2023

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1 Distribution of Observations: Funnel Plots

To illustrate the distribution of observations, we produce a funnel chart by plotting the partial correlation against precision (the inverse of its standard error).[1] By construction, estimates with a larger standard error (less precision) are spread at the bottom of the graph while those that are more precise form the top of the funnel. In the absence of publication selection bias, the funnel plot should be symmetric, with observations randomly distributed around the "true" effect (Egger et al., 1997; Stanley, 2007; Stanley and Doucouliagos, 2012).

We have *ex-ante* expectations about the selective report of scholars and researchers about higher or lower risks of conflicts, depending on the transmission channels. We may suspect lower risks of conflicts in case of positive agricultural shocks (AS+) (e.g., increase in demand and international producers' prices, exceptional rainfalls). On the contrary, we may suspect higher risks of conflicts in case of negative agricultural shocks (AS-) (e.g., droughts, floods, rain deficiencies), and positive hydrocarbon/mineral shocks (HS+) (e.g., increase in mineral or oil international prices, subsidies to mining concessions). As AS- represent more 42.6% of the 2,464 observations, we would expect either a funnel plot centered close to zero and/or an asymmetry towards higher risks of conflicts.

Figure 1 highlights a mix of both intuitions; the chart for the baseline sample suggests potentially null average genuine effects as the more precise estimates (at the top of the funnel) are closely distributed around zero. Moreover, the funnel appears slightly right-skewed (i.e., an asymmetry towards higher risks of conflict) for less precise estimates (at the bottom of the funnel), indicating the likelihood of publication selection bias, altogether with potential genuine effects. Switching to subgroups analysis, we find a right-skewed distribution (i.e., an asymmetry towards higher risks of conflict) when focusing on the of impact of AS-, a surprisingly slightly left-skewed distribution (i.e., an asymmetry towards lower risks of conflict)

[1] Partial correlation is computed as $r = \frac{t}{\sqrt{t^2+df}}$, where t is the t-statistic of the regression coefficient and df denotes the degrees of freedom. Partial correlation coefficients measure the strength and direction of the association between potential determinants of conflicts and conflicts' outcomes, holding all other factors constant. The standard error of the partial correlation is computed as $\sqrt{(1-r^2)/df}$ in line with Stanley and Doucouliagos (2012).

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when focusing on the impact of HS+, and a slightly right-skewed distribution when focusing on the impact of AS+. This comforts us on the importance of controlling for mechanisms encompassed by authors (e.g., poverty related, rent capture) to assess the impact of local shocks on conflicts. For AS- and possibly HS+, the skewness is more pronounced for less precise estimates (at the bottom of the funnel), indicating the likelihood of publication selection bias. For AS+, a (left-side) skewness exists also for more precise estimates, indicating potentially the presence of genuine lower risks of conflicts despite the overall slightly right-skewed asymmetry.

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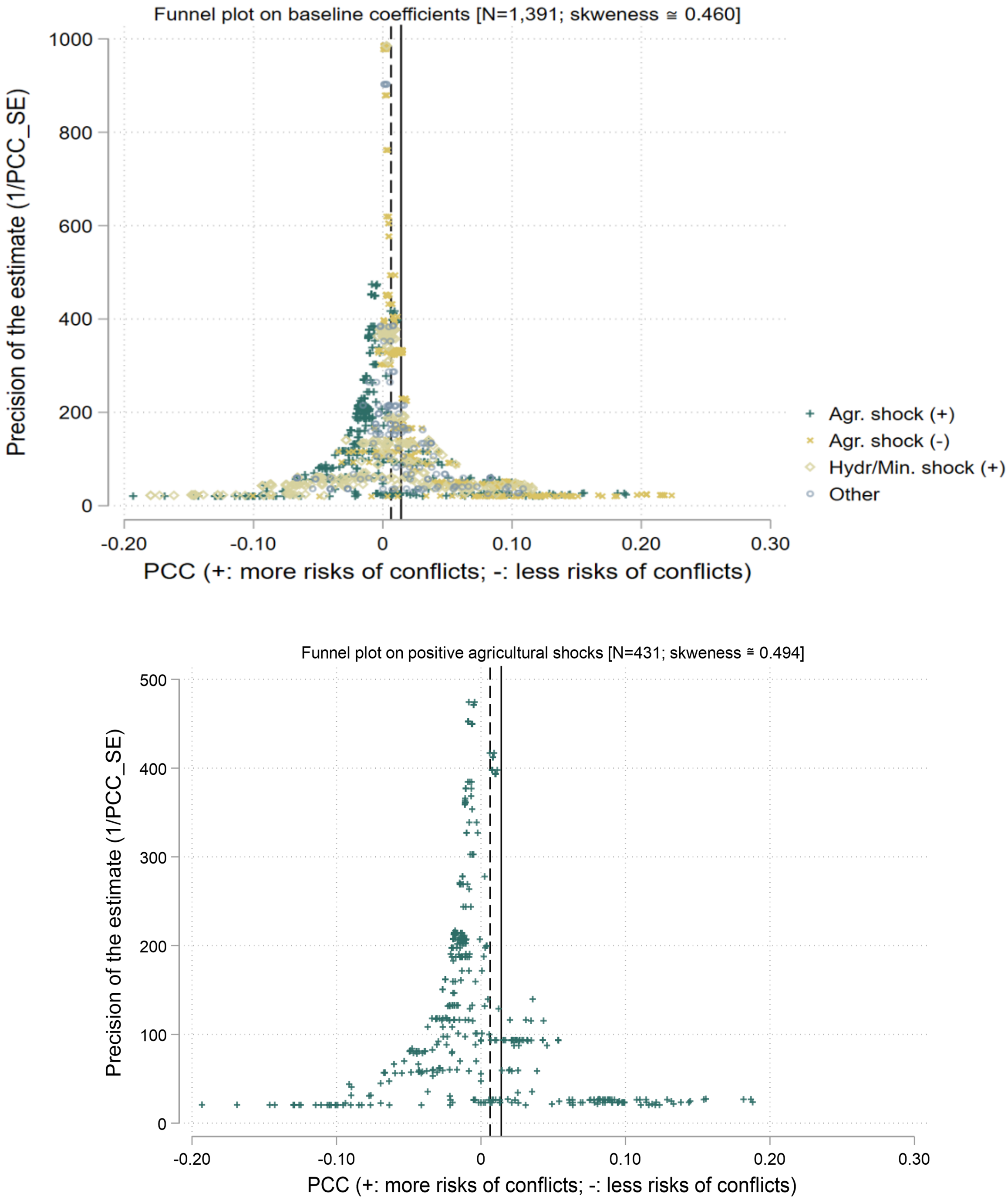

Notes: The dashed vertical line shows the weighted average partial correlation (0.008, see Figure from the Appendices section), using inverse variance weights. Precision is measured as the inverse of the estimated standard error of the partial correlations. Upper panel: baseline sample (1,397 obs.). Lower panel: baseline sample of positive agricultural shocks (431 obs.). *Source: Authors' compilation from MRA database.*

Figure 1: Partial Correlations Between Potential Channel of Transmission and Risks of Conflicts

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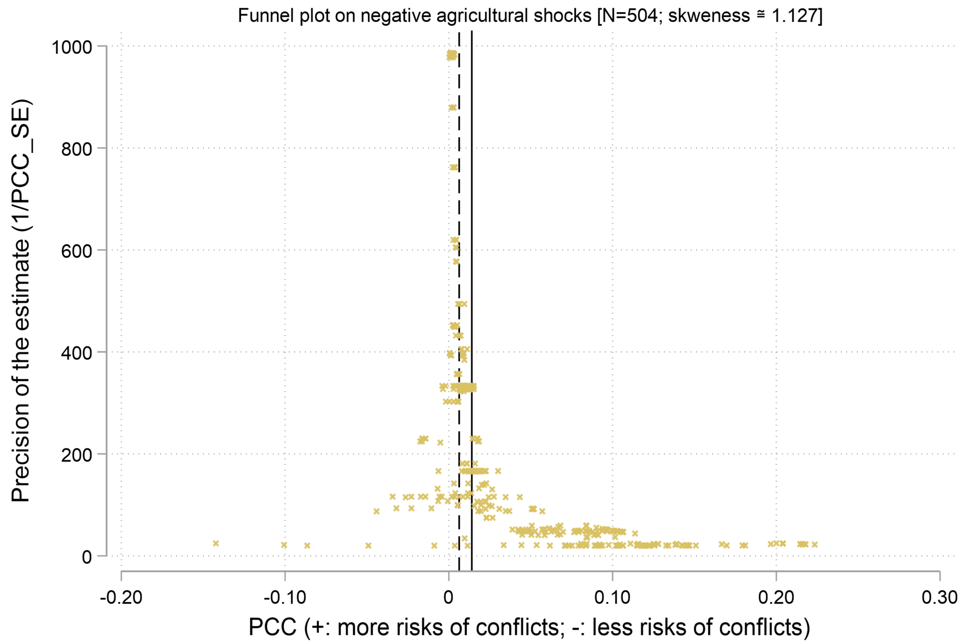

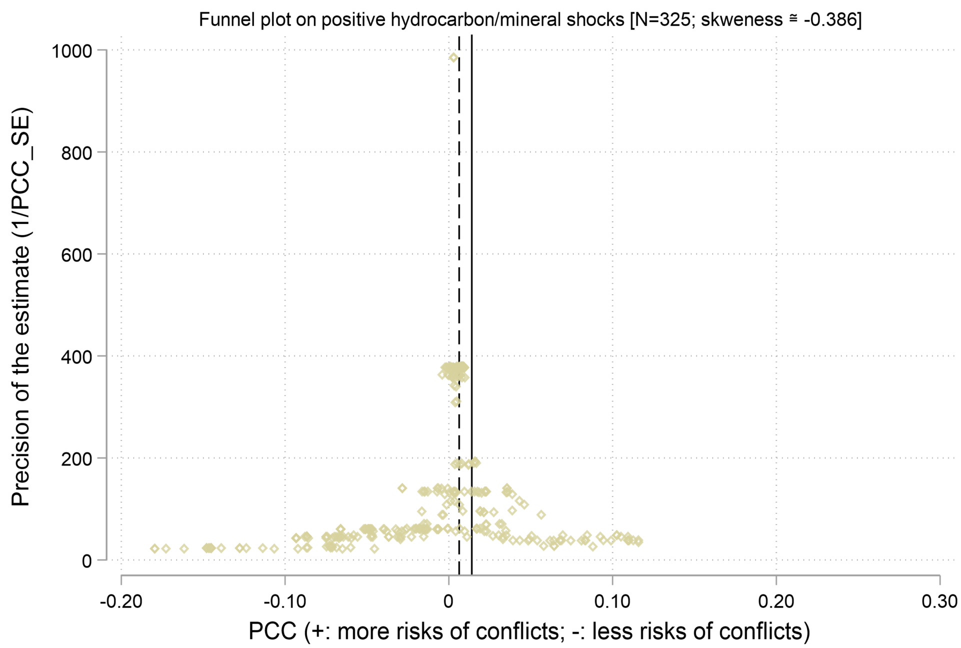

Notes: The dashed vertical line shows the weighted average partial correlation (0.008, see Figure from the Appendices section), using inverse variance weights. Precision is measured as the inverse of the estimated standard error of the partial correlations. Upper panel: baseline sample of negative agricultural shocks (504 obs.). Lower panel: baseline sample of positive hydrocarbon/mineral shocks (325 obs.). *Source: Authors' compilation from MRA database.*

Table 1 continued: Partial Correlations Between Potential Channel of Transmission and Risks of Conflicts

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2 Bayesian Model: Do the Scientific Publication Process, Data, and Methodological Choices Affect the Results?

2.1 Model Estimated and Description of the Moderators

In order to investigate systematic differences among the reported estimates, we select and present some key study characteristics (also called *moderators*) that are likely to drive the results. We code 41 variables according to the following categories: transmission channels, mechanisms and interactive models, publication outlet, geography, model characteristics, conflict characteristics, measures of shocks, and model specifications. Descriptive statistics of the moderators are detailed in Table A3 in the Appendix. For the model specification, we follow Stanley and Doucouliagos (2012):

$$PCC_{ij} = \beta_0 + \beta_1 SE^{pcc}_{ij} + \sum_{k=2}^{41} \beta_k x^{'}_{ij} + \varepsilon_{ij} \tag{1}$$

where PCC is the partial correlation coefficient between local income shocks and conflicts' outcome of the i^{th} estimate from the j^{th} study, SE^{pcc} denotes the standard error of the PCC, and ε_{ij} is the error term. The vector $x^{'}_{ij}$ stands for a set of variables capturing study- and regression-specific characteristics associated with the j^{th} estimate as discussed in Section 5.1, with potential bearing on risks of conflicts. In other words, heterogeneity introduced and detailed below can be identified and quantified by the coefficients β_k.

Publication Outlet

Differences in publication processes may explain the heterogeneity of estimates. We address this concern through several controls. First, a stricter publishing process, indicated by SJR score[2] and top economics/political science journals, can limit imprecision in estimates. Sec-

[2] Scimago Journal & Country Rank (SJR): `https://www.scimagojr.com/journalrank.php`.

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ond, conflict-specialized journals may be more willing to publish counter-intuitive results with careful contextual analysis and reviewed by specialized peers. Third, sensitivity and robustness checks can identify or mitigate significant relationships. Fourth, older studies may have less precise estimates due to the availability of improved disaggregated data and statistical methodologies in recent years.

Geography

A commonly held limitation of the conflict literature is that phenomena applying to one country or region hardly apply to the rest of the world since the formation of armed groups is often rooted in the long history of nation-building (de Mesquita, 1985; Cramer, 2002; Michalopoulos and Papaioannou, 2020). This point seems likely given our sample of studies: 55% of the selected estimates focus at least partially on a panel of African countries, and half of the selected articles focus on a single country. We introduce several geography covariates to control for this potential source of heterogeneity. Specifically, we include dummy variables to assess whether estimates from country case studies or works on specific geographic regions explain heterogeneity among results.

Model Characteristics

To explain heterogeneity, model construction choices can play a role. First, we test the impact of estimator choices. Maximum-likelihood (MLE) and Ordinary Least Squares (OLS) are commonly used. We create a dummy variable taking the value *one* for MLE estimators (Logit, Negative binomial or Poisson pseudo maximum-likelihood), and *zero* otherwise. Second, specific effects (fixed, random, or mixed) can reduce unobserved heterogeneity. We create a dummy taking the value *one* if specific effects are included, and *zero* otherwise. Third, clustering can affect statistical inference, so we include a dummy variable indicating whether estimates are clustered on the unit of reference. Fourth, we indicate whether the period of interest is before or after the end of the Cold War (i.e., after 1991). Finally, we include

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information on the level of disaggregation of the estimates (regions, grid cells, etc.). Several reviews of the literature suggest using small geographic units and quasi-experimental design to avoid biases arising from unobserved heterogeneity or competing mechanisms (Collier and Hoeffler, 2007; Blattman and Miguel, 2010; Couttenier and Soubeyran, 2015). However, these gains for the identification strategy may also depend on the existence of subnational root causes of conflict and the degree of precision of the data at that scale (for a discussion, see Laville, 2019).To test the impact of spatial unit size, we include a dummy variable for grid cells less than or equal to 0.5°x0.5° at the equator (approx. 55km $\times$ 55km), and the natural logarithm of the sample size.

Conflict Characteristics

We use several variables to account for heterogeneity in estimates due to differences in the definition of conflict outcomes. First, we include a dummy variable indicating whether the regression relies on data from UCDP/PRIO (Sundberg and Melander, 2013) or ACLED (Raleigh et al., 2010). Indeed, their respective definition of violent phenomena and potential omission, inflation, or misrepresentation of events could systematically influence the literature due to their widespread use (Miller et al., 2022). Second, we control for the type of conflict outcome using three dummy variables. These indicate estimates of conflict incidence (total number of conflicts per day/month/year or whether at least one conflict is observed), onset (only the starting day/month/year of conflict), or duration (number of days/months/years of active conflict). Third, we include a dummy variable to indicate the spatial dimension of the dependent variable, which is either local (below Admin1 level or at small grids level) or larger (above Admin2 level or at large grids level). Fourth, we include a dummy variable to indicate whether the conflict involved human casualties, indicating a relatively more intense form of conflict. Finally, we control for the type of conflict by including dummy variables that indicate whether the authors studied armed conflicts, crimes, social unrest, and/or violence against civilians. These variables allow us to explore systematic differences between studies

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and help to account for heterogeneity in the literature.

Measures of Shocks

How the authors measure income shocks may influence their results. First, we include a dummy variable indicating if the estimate uses a quasi-experimental design, namely if a measure of shock (e.g., prices variations, rainfall variation, floods, etc.) is interacted with a measure of resource endowment in the cell (e.g., production areas of coal, coffee intensity, oil and gas reserves, etc.). Second, following Dal Bó and Dal Bó (2011) and Dube and Vargas (2013), we include a dummy variable indicating if the shock specifically concerns a labor-intensive agricultural commodity.[3] Agricultural shocks that do not concern the production of a labor-intensive good include general climatic shocks that could influence labor-intensive and capital-intensive productions simultaneously, shocks that concern the livestock sector,[4] shocks on consumer commodity prices, and shocks related to resource scarcity. Finally, we separate climatic shocks, price shocks and other types of shocks using dummy variables.

Model Specifications

Estimates can be sensitive to the choice of explanatory variables. In a sensitivity analysis of the conflict literature, Hegre and Sambanis (2006) identify a robust correlation between conflict onset and several variables including low per capita income, slow income growth, recent political instability, large population size, and war-prone neighbors. As noted by Blattman and Miguel (2010), the inclusion of such correlates in conflict models may bias other estimates in unknown directions due to endogeneity or insufficient knowledge about

[3]Extending the labor-intensive commodity shock variable to the case of mineral resources presented some challenges. One issue is that a resource can be labor-intensive in one country but not in another, depending on factors such as infrastructure. Another challenge is the potential for an adverse selection bias, as we rely on authors' knowledge of labor-intensity in commodity production. For instance, Corvalan and Pazzona (2019) examine the link between copper market shocks and crime in Chile, but do not specify the labor-intensity of copper production. As a result, we limit our analysis to agricultural goods, which involve fewer subjective choices in our coding strategy.

[4]We separate livestock sector shocks to ensure variable homogeneity since they are relatively less labor-intensive compared to agriculture, and their effects on the labor market are less direct due to the creation or abandonment of an entire herd not being immediate.

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the mechanisms involved. We control for the inclusion of these correlates (population size, GDP, past conflicts, and neighborhood conflicts) as control variables using dummy variables.

2.2 Estimation Technique and Results

We ideally want to include all 41 moderators in Equation 1. However, too many covariates increase the risk of false positive conclusions (Thompson and Higgins, 2002), and the inclusion of the wrong variables may lead to misspecification bias and invalid inference. Thus, we face a fundamental issue of model uncertainty regarding the variables to include in estimating Equation 1. Two popular strategies to address this issue are model selection and model averaging (Steel, 2020). Stepwise regression is the easiest and most used approach for model selection. However, this method may erroneously exclude important variables in sequential t-tests, and it does not account for the selection process when presenting the results of the final equation. To avoid depending on the selected model, we use the Bayesian Model Averaging (BMA) approach, which considers all possible models (Havranek et al., 2017, 2018; Zigraiova et al., 2021). The goal of BMA is to find the best possible approximation of the distribution of regression parameters by running regressions based on different subsets of moderators. Since we consider 41 variables, this yields 2^{41} possible models to estimate. We therefore apply the Markov chain Monte Carlo algorithm, which approximates the model space and walks the part that contains the models with the highest posterior model probabilities (PMP), which measures the 'goodness of fit' of each model with the data. For each variable in the model, BMA reports three parameters: posterior mean, posterior standard deviation and posterior inclusion probability (PIP). PIP aggregates the PMPs of all the models in which the variable is included. A PIP above 0.5 is usually regarded as the threshold to include variables in the model (Jeffreys, 1961; Eicher et al., 2011).

Figure 2 is a graphical representation of the BMA results for the whole sample of 2,464 regressions. The vertical axis lists the explanatory variables sorted by PIP in descending order. The horizontal axis is the PMP of each model sorted in ascending order. The blue (dark)

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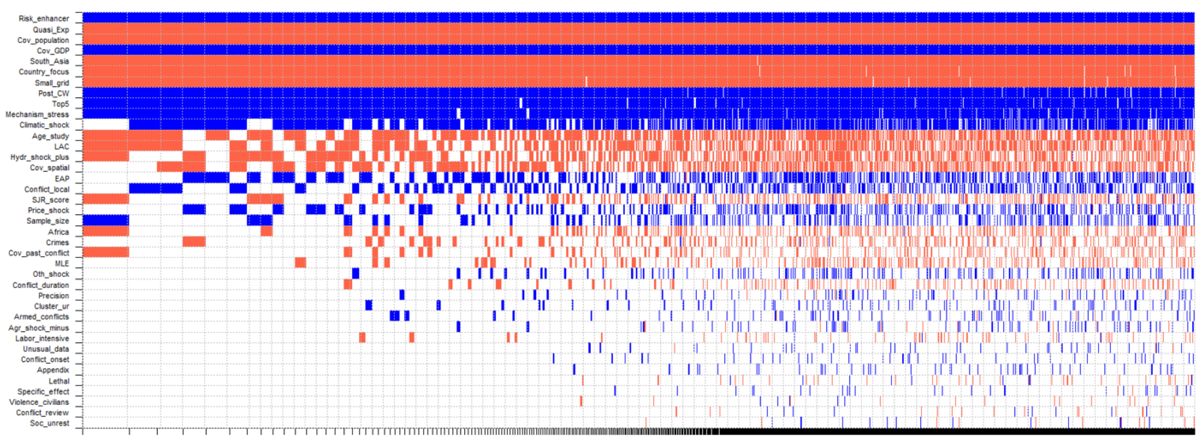
color indicates the positive sign of the variable in the model, and the red color (light) denotes the negative sign of the variable. The blank cell suggests that the variable is excluded from the regression model. Figure 2 shows that nearly one-third of the variables are included in the best model and that their signs are robustly consistent across different models. Figure 3 is a graphical representation of our BMA results for AS+ (a), AS- (b), and HS+ (c). Approximately one-third of the moderators are included in the best models for agricultural shocks, compared to half of them for shocks in the extractive sector. However, fewer moderators are tested for HS+, which is most likely due to the smaller number of observations in this sub-sample. Overall, their effect's sign also appears consistent across different models. We note that they are mainly negative for AS- studies, positive for HS+ studies, and nuanced for AS+ studies.



Notes: The figure depicts the results of Bayesian Model Averaging. The explanatory variables are ranked according to their posterior inclusion probabilities from the highest on the top to the lowest at the bottom. The horizontal axis shows the values of cumulative posterior probability. Blue and red colours denote the positive and negative sign of the estimated parameter of explanatory variable, respectively. No colour means the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 1. All variables are described in Table A3 in the Appendix. *Source: Authors' compilation from MRA database.*

Figure 2: Model Inclusion in Bayesian Model Averaging [Total Sample]

Table 1 presents the empirical results of BMA for the whole sample of 2,464 regressions. We also report the OLS results using the variables from BMA with PIP higher than 0.5.

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When interpreting the BMA results, we follow Jeffreys (1961), who considers that the value of PIP indicates a decisive effect if it exceeds 0.99, a strong effect if it is between 0.95 and 0.99, a positive effect if it is between 0.75 and 0.95, and a weak effect if it is between 0.5 and 0.75. The publication bias term in Table 1 is positive and statistically significant at the 0.10 level after controlling for our set of moderators. It confirms that the baseline result is not a spurious outcome caused by omitted variables and confirms that the literature suffers from publication selection bias. Fourteen variables present a PIP higher than 0.5, indicating that they are relevant for explaining the differences in the estimates. We focus on the variables for which we have the most robust evidence across the two specifications: at least a strong PIP in BMA, and a significance level of at least 10% in OLS. We find that studies testing theoretically detrimental mechanism, introducing interactions with a risk enhancer, or involving a climatic income shock find a higher local risk of conflict subsequent to income shocks, underscoring the importance of controlling for such moderators when studying the relationship between income shocks and conflict. Moreover, studies published in top-tier journals and those controlling for GDP tended to report a higher risk of conflict. In contrast, studies focusing on South Asian countries, controlling for population size, using quasi-experimental frameworks or studying small grid cells tended to report a lower risk of conflict.

Table 2 reports the results of the BMA and OLS for the sub-samples of AS+ (710 regressions), AS- (1,049 regressions), and HS+ (543 regressions) studies. The results we obtain for publication bias after controlling for our set of moderators confirms the presence of a substantial positive publication bias in the literature focusing on AS-.[5] We find that AS+ studies specifically testing for stressful mechanisms[6] or introducing interactions with a risk enhancer find a higher risk of conflict. All things being equal, they also find a higher risk of conflict when they go through a stricter publishing process, and a lower risk of conflict when they focus on Latin America, Africa or South Asia. Studies encompassing negative

[5]The statistically significant and negative coefficients obtained for AS+ and HS+ are difficult to interpret due to the large number of moderators that condition them.

[6]A few studies of AS+ test agitating mechanisms through rapacity effects.

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agricultural shocks (AS-) approaching income shocks through climatic events find a higher risk of conflict. They also find a stronger association between income shocks and local criminality (e.g., robberies, property trespassing, assaults). Finally, studies published in journals with higher SJR scores or specializing in conflict analysis, which control for population size, and which are implemented below Admin1 level or at a small grid cell level tend to report a smaller risk of conflict. Studies focusing on positive hydrocarbon/mineral shocks (HS+) find a lower risk of conflict when they are country case studies or encompass larger samples.

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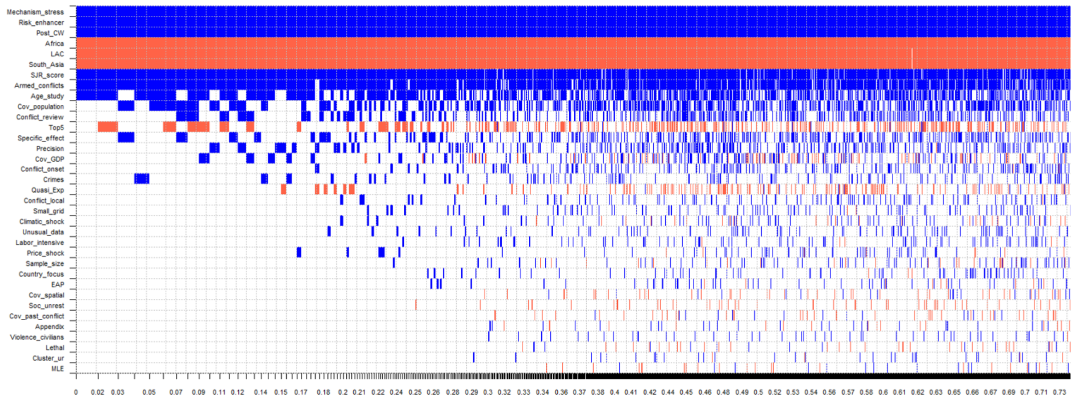
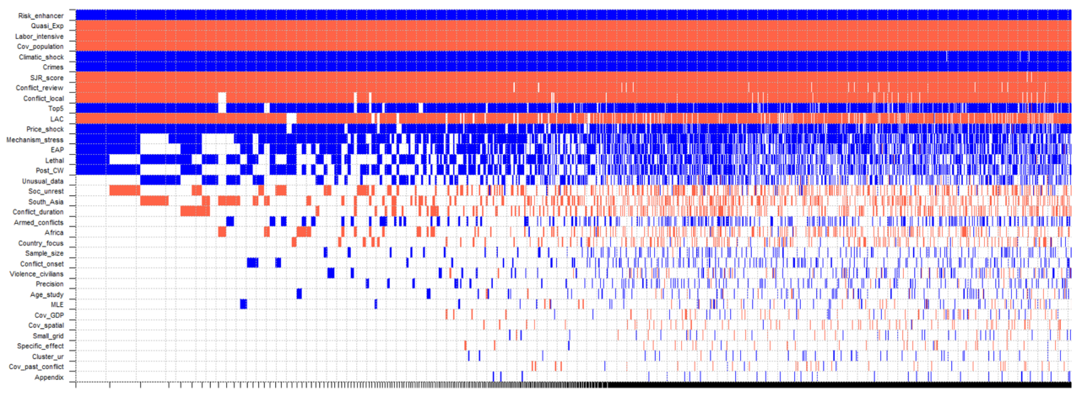
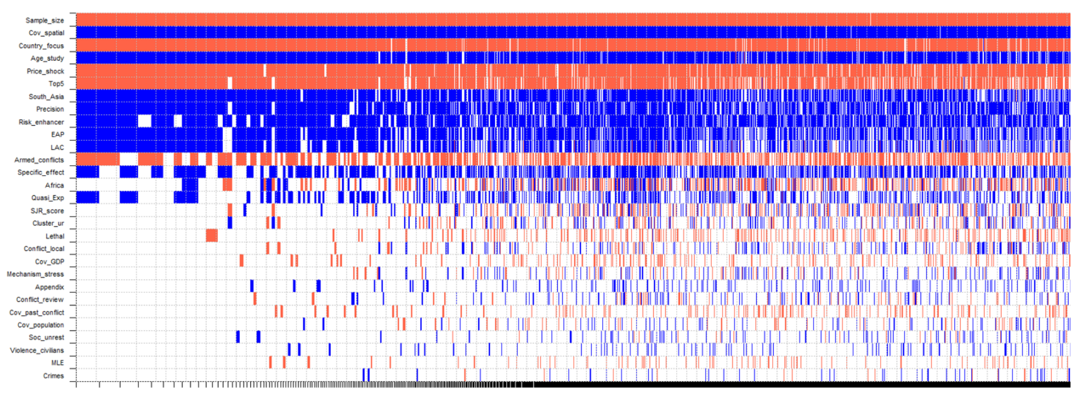
(a) Positive Agricultural Shocks (AS+)



(b) Negative Agricultural Shocks (AS-)



(c) Positive Hydrocarbon and Mineral Shocks (HS+)



Notes: The figure depicts the results of Bayesian Model Averaging. The explanatory variables are ranked according to their posterior inclusion probabilities from the highest on the top to the lowest at the bottom. The horizontal axis shows the values of cumulative posterior probability. Blue and red colours denote the positive and negative sign of the estimated parameter of explanatory variable, respectively. No colour means the corresponding explanatory variable is not included in the model. Numerical results are reported in Table 2. All variables are described in Table A3 in the Appendix. *Source: Authors' compilation from MRA database.*

Figure 3: Model Inclusion in Bayesian Model Averaging [Sub-samples]

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Table 1: Explaining Heterogeneity in the Estimated Effects of Income Shocks on Conflicts [BMA - Total Sample]

	Full sample					
	BMA			OLS		
	Post Mean	Post SD	PIP	Coef.	SE	p-Value
(i) Baseline						
Publication bias ($\beta1$)	**0.881**	**NA**	**1.000**	**0.750**	**0.406**	**0.077**
Precision ($\beta0$)	0.000	0.002	0.061	0.004	0.004	0.112
(ii) Transmission channels						
Positive agricultural shock (Ref.)						
Negative agricultural shock	2.0E-04	0.001	0.053	-	-	-
Positive hydrocarbon shock	**-0.002**	**0.003**	**0.551**	-0.002	0.002	0.369
Other shock	3.5E-04	0.001	0.119	-	-	-
(iii) Mechanisms and interactive models						
Other mechanisms (Ref.)						
Mechanism stressful	**0.006**	**0.001**	**0.976**	**0.006**	**0.002**	**0.001**
Others (Ref.)						
Risk enhancer	**0.004**	**0.000**	**1.000**	**0.004**	**0.002**	**0.097**
(iv) Publication outlet						
No top 5 reviews (Ref.)						
Top 5	**0.006**	**0.003**	**0.984**	**0.005**	**0.002**	**0.002**
No conflict reviews (Ref.)						
Conflict review	-4.1E-06	0.000	0.015	-	-	-
Core results (Ref.)						
Appendix results	1.2E-05	0.000	0.025	-	-	-
Continuous variables						
Age of study	**-3.8E-04**	**0.000**	**0.678**	-0.001	0.000	0.116
SJR score	-1.0E-04	0.000	0.310	-	-	-
(v) Geography						
No country focus (Ref.)						
Country focus	**-0.009**	**0.003**	**0.994**	-0.005	0.004	0.139
Worldwide (Ref.)						
Region: Africa	-0.001	0.002	0.235	-	-	-
Region: East Asia Pacific (EAP)	0.003	0.004	0.453	-	-	-
Region: Latin America & the Caribbean (LAC)	**-0.005**	**0.004**	**0.583**	**-0.007**	**0.002**	**0.001**
Region: South Asia	**-0.023**	**0.006**	**0.998**	**-0.024**	**0.010**	**0.023**
(vi) Model characteristics						
No MLE (Ref.)						
Maximum likelihood estimator	-3.8E-04	0.001	0.153	-	-	-
No specific effects (Ref.)						
Specific effects	1.5E-05	0.000	0.017	-	-	-
No cluster unit reference (Ref.)						
Cluster unit reference	8.0E-05	0.000	0.061	-	-	-
Pre cold war (Ref.)						
Post cold war	**0.003**	**0.001**	**0.990**	0.003	0.003	0.244
No small grids (Ref.)						
Small grids	**-0.008**	**0.004**	**0.994**	**-0.009**	**0.003**	**0.008**
Continuous variable						
Sample size	1.9E-04	0.000	0.263	-	-	-
(vii) Conflict characteristics						
Usual conflict data (Ref.)						
Unusual conflict data	6.0E-05	0.000	0.034	-	-	-
Conflict incidence (Ref.)						
Conflict duration	-8.0E-05	0.000	0.100	-	-	-
Conflict onset	1.4E-05	0.000	0.028	-	-	-
No local conflicts (Ref.)						
Conflict local	0.003	0.004	0.367	-	-	-
Non lethal (Ref.)						
Lethal	-1.9E-05	0.000	0.023	-	-	-
Others (Ref.)						
Armed conflicts	6.2E-05	0.000	0.060	-	-	-
Crimes	-0.001	0.002	0.197	-	-	-
Social unrests	-5.9E-06	0.000	0.013	-	-	-
Violence against citizens	-1.1E-05	0.000	0.015	-	-	-
(viii) Measures of shocks						
No quasi experimental (Ref.)						
Quasi experimental	**-0.006**	**0.001**	**1.000**	**-0.005**	**0.003**	**0.043**
No labor intensive (Ref.)						
Labor intensive resources	-5.9E-05	0.000	0.047	-	-	-
Others (Ref.)						
Climatic shock	**0.003**	**0.002**	**0.772**	**0.003**	**0.002**	**0.082**
Price shock	0.001	0.002	0.302	-	-	-
(ix) Model specification						
No past conflict (Ref.)						
Control for past conflicts	-4.5E-04	0.001	0.169	-	-	-
No spatial factor (Ref.)						
Control for conflict spatial factor	-0.003	0.003	0.534	-0.005	0.003	0.132
No population (Ref.)						
Control for population	**-0.003**	**0.000**	**1.000**	**-0.003**	**0.002**	**0.038**
No GDP (Ref.)						
Control for GDP	**0.006**	**0.001**	**0.999**	**0.007**	**0.002**	**0.001**

Models are estimated on the whole sample of 2,464 observations and 64 studies. The weight used is the inverse of SE^{pcc}. The dependent variable is the partial correlation between shocks and conflicts. Bayesian model averaging (BMA) and OLS are used, with BMA employing the unit information and the dilution prior (UIP g-prior; uniform model prior on the BMS package by Zeugner and Feldkircher (2015)). The frequentist check (OLS) only includes explanatory variables with a PIP $\geq$ 0.50. Standard errors are clustered at the study level. Explanatory variables with a PIP $\geq$ 0.50 (BMA) and/or statistically significant at 10% or less (OLS) are in bold. SD, SE and PIP stand for standard deviation, standard error and posterior inclusion probability, respectively. *Source: Authors' compilation from MRA database.*

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Table 2: Explaining Heterogeneity in the Estimated Effects of Income Shocks on Conflicts [BMA - Sub-Samples]

	Positive Agricultural Shocks (AS+)						Negative Agricultural Shocks (AS-)						Positive Hydrocarbon and Mineral Shocks (HS+)					
	BMA			OLS			BMA			OLS			BMA			OLS		
	Post Mean	Post SD	PIP	Coef.	SE	p-Value	Post Mean	Post SD	PIP	Coef.	SE	p-Value	Post Mean	Post SD	PIP	Coef.	SE	p-Value
(i) Baseline																		
Publication bias ($\beta1$)	**-0.522**	**NA**	**1.000**	**-0.583**	**0.329**	**0.090**	**1.351**	**NA**	**1.000**	**1.168**	**0.234**	**0.000**	**-3.100**	**NA**	**1.000**	**-2.870**	**0.718**	**0.002**
Precision ($\beta0$)	0.005	0.010	0.225	0.013	0.009	0.145	0.001	0.005	0.083	0.004	0.012	0.728	**0.115**	**0.073**	**0.802**	**0.109**	**0.039**	**0.014**
(ii) Mechanisms and interactive models																		
Other mechanisms (Ref.)																		
Mechanism stressful	**0.045**	**0.005**	**1.000**	**0.044**	**0.005**	**0.000**	**0.012**	**0.009**	**0.703**	0.015	0.012	0.204	-4.0E-04	0.012	0.107	-	-	-
Others (Ref.)																		
Risk enhancer	**0.016**	**0.001**	**1.000**	**0.016**	**0.004**	**0.001**	**0.002**	**0.000**	**1.000**	0.002	0.002	0.160	**0.002**	**0.001**	**0.801**	0.002	0.002	0.315
(iii) Publication outlet																		
No top 5 reviews (Ref.)																		
Top 5	-0.003	0.005	0.306	-	-	-	**0.054**	**0.024**	**0.918**	**0.063**	**0.015**	**0.000**	**-0.034**	**0.027**	**0.859**	**-0.027**	**0.005**	**0.000**
No conflict reviews (Ref.)																		
Conflict review	0.004	0.007	0.310	-	-	-	**-0.017**	**0.005**	**0.987**	**-0.015**	**0.003**	**0.000**	0.001	0.005	0.095	-	-	-
Core results (Ref.)																		
Appendix results	0.000	0.000	0.028	-	-	-	0.000	0.000	0.021	-	-	-	0.001	0.005	0.097	-	-	-
Continuous variables																		
Age of study	**0.001**	**0.001**	**0.646**	0.001	0.001	0.154	0.000	0.000	0.064	-	-	-	**0.009**	**0.005**	**0.936**	**0.008**	**0.001**	**0.000**
SJR score	**0.001**	**0.000**	**0.964**	**0.001**	**0.000**	**0.019**	**-0.003**	**0.001**	**0.999**	**-0.004**	**0.001**	**0.000**	0.000	0.002	0.229			
(iv) Geography																		
No country focus (Ref.)																		
Country focus	0.000	0.002	0.041	-	-	-	-0.001	0.003	0.119	-	-	-	**-0.064**	**0.025**	**0.971**	**-0.061**	**0.012**	**0.000**
Worldwide (Ref.)																		
Region: Africa	**-0.032**	**0.006**	**1.000**	**-0.037**	**0.006**	**0.000**	-0.001	0.002	0.157	-	-	-	0.006	0.045	0.407	-	-	-
Region: EAP	0.000	0.003	0.038	-	-	-	**0.008**	**0.007**	**0.610**	**0.010**	**0.002**	**0.000**	**0.064**	**0.057**	**0.786**	**0.056**	**0.014**	**0.001**
Region: LAC	**-0.039**	**0.007**	**1.000**	**-0.041**	**0.007**	**0.000**	**-0.017**	**0.009**	**0.884**	**-0.015**	**0.005**	**0.007**	**0.036**	**0.051**	**0.669**	**0.035**	**0.004**	**0.000**
Region: South Asia	**-0.038**	**0.007**	**1.000**	**-0.042**	**0.006**	**0.000**	-0.005	0.010	0.271	-	-	-	**0.092**	**0.055**	**0.841**	**0.101**	**0.015**	**0.000**
(v) Model characteristics																		
No MLE (Ref.)																		
Maximum likelihood estimator	-2.8E-06	0.000	0.020	-	-	-	5.3E-05	0.001	0.052	-	-	-	-4.3E-04	0.002	0.058	-	-	-
No specific effects (Ref.)																		
Specific effects	0.003	0.005	0.264	-	-	-	-2.2E-05	0.000	0.024	-	-	-	**0.056**	**0.057**	**0.600**	**0.048**	**0.021**	**0.042**
Others (Ref.)																		
Cluster unit reference	1.1E-05	0.000	0.023	-	-	-	1.5E-05	0.000	0.024	-	-	-	-0.001	0.012	0.162	-	-	-
Pre cold war (Ref.)																		
Post cold war	**0.006**	**0.001**	**1.000**	0.006	0.004	0.114	**0.003**	**0.003**	**0.515**	**0.005**	**0.001**	**0.000**	-	-	-	-	-	-
No small grids (Ref.)																		
Small grids	2.9E-04	0.001	0.071	-	-	-	2.7E-05	0.001	0.033	-	-	-	-	-	-	-	-	-
Continuous variable																		
Sample size	2.0E-06	0.000	0.048	-	-	-	8.6E-05	0.000	0.095	-	-	-	**-0.011**	**0.004**	**0.999**	**-0.009**	**0.002**	**0.001**
(vi) Conflict characteristics																		
Usual conflict data (Ref.)																		
Unusual conflict data	2.4E-04	0.001	0.062	-	-	-	0.002	0.004	0.367	-	-	-	-	-	-	-	-	-
Conflict incidence (Ref.)																		
Conflict duration	-	-	-	-	-	-	-1.7E-04	0.000	0.219	-	-	-	-	-	-	-	-	-
Conflict onset	4.2E-04	0.001	0.126	-	-	-	5.9E-05	0.000	0.095	-	-	-	-	-	-	-	-	-
No local conflicts (Ref.)																		
Conflict local	3.2E-04	0.001	0.075	-	-	-	**-0.012**	**0.004**	**0.965**	**-0.015**	**0.003**	**0.000**	0.001	0.009	0.140	-	-	-
Non lethal (Ref.)																		
Lethal	-6.3E-06	0.001	0.025	-	-	-	**0.004**	**0.005**	**0.558**	**0.004**	**0.002**	**0.019**	-0.001	0.002	0.143	-	-	-
Others (Ref.)																		
Armed conflicts	**0.005**	**0.002**	**0.910**	**0.005**	**0.001**	**0.000**	0.001	0.001	0.205	-	-	-	**-0.001**	**0.001**	**0.603**	**-0.002**	**0.001**	**0.007**
Crimes	0.001	0.002	0.120	-	-	-	**0.028**	**0.006**	**0.999**	**0.031**	**0.005**	**0.000**	2.2E-04	0.003	0.036	-	-	-
Social unrests	-1.2E04	0.001	0.030	-	-	-	-0.001	0.003	0.273	-	-	-	1.4E-04	0.001	0.063	-	-	-
Violence against citizens	7.1E-05	0.001	0.028	-	-	-	2.1E-04	0.002	0.092	-	-	-	3.1E-04	0.002	0.063	-	-	-
(vii) Measures of shocks																		
No quasi experimental (Ref.)																		
Quasi experimental	-0.001	0.002	0.115	-	-	-	**-0.004**	**0.001**	**1.000**	-0.004	0.002	0.102	0.010	0.014	0.404	-	-	-
No labor intensive (Ref.)																		
Labor intensive resources	2.1E-04	0.001	0.057	-	-	-	**-0.004**	**0.001**	**1.000**	-0.004	0.003	0.127	-	-	-	-	-	-
Others (Ref.)																		
Climatic shock	1.8E-04	0.001	0.062	-	-	-	**0.007**	**0.001**	**0.999**	**0.007**	**0.002**	**0.002**	-	-	-	-	-	-
Price shock	1.2E-04	0.001	0.051	-	-	-	**0.014**	**0.008**	**0.865**	**0.014**	**0.006**	**0.015**	**-0.074**	**0.039**	**0.927**	**-0.063**	**0.017**	**0.003**
(viii) Model specification																		
No past conflict (Ref.)																		
Control for past conflicts	-1.8E-05	0.000	0.029	-	-	-	-1.0E-05	0.000	0.024	-	-	-	-0.001	0.005	0.093	-	-	-
No spatial factor (Ref.)																		
Control for conflict spatial factor	-4.6E-05	0.001	0.029	-	-	-	-9.1E-05	0.001	0.037	-	-	-	**0.017**	**0.005**	**0.997**	0.016	0.010	0.118
No population (Ref.)																		
Control for population	2.0E-03	0.003	0.481	-	-	-	**-0.002**	**0.000**	**1.000**	**-0.002**	**0.001**	**0.098**	2.6E-04	0.008	0.079	-	-	-
No GDP (Ref.)																		
Control for GDP	2.4E-05	0.002	0.199	-	-	-	-6.7E-05	0.001	0.042	-	-	-	-0.005	0.016	0.111	-	-	-

Notes: The analysis is based on three subsamples: AS+ (710 observations and 24 studies), AS- (1,049 observations and 35 studies), and HS+ (543 observations and 14 studies). The weights are the inverse of SE^{pcc}. The dependent variable is the partial correlation between the type of shock and conflicts. Bayesian model averaging (BMA) employs the unit information and the dilution prior (UIP g-prior; uniform model prior on the BMS package by Zeugner and Feldkircher (2015)) suggested by George (2010). The frequentist check (OLS) includes only explanatory variables with a PIP above 50% (≥ 0.50) in the BMA and is estimated using clustered standard errors (cluster at the study level). In bold, explanatory variable with a PIP above 50% (≥ 0.50) (BMA) and/or statistically significant at 10% or less (OLS). SD, SE and PIP stand for standard deviation, standard error and posterior inclusion probability, respectively. *Source: Authors' compilation from MRA database.*

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3 Detailed Characteristics of Individual Studies in the Meta-Sample

Table 3: Characteristics of Individual Studies

#	Study	Review	SJR score	Regressions #	Regressions % total	Interaction #	Interaction %	Subgroup	Mechanism(s)	Time period(s)	Region	Country focus
1	Abidoye and Calì (2021)	Journal of African Economies	0.520	22	0.9%	0	0.0%	AS+; AS-	Pacifying; stressful	2004-2011	SSA	Nigeria
2	Acharya et al. (2020)	Journal of Theoretical Politics	0.954	10	0.4%	10	0.9%	AS+	Pacifying	2000-2012	SSA	Somalia (Somaliland, Puntland)
3	Ahrens (2015)	Peace Economics, Peace Science and Public Policy#	0.186	4	0.2%	0	0.0%	AS+	Pacifying	1992-2010	SSA	No
4	Almer et al. (2017)	Journal of Environmental Economics and Management	2.198	162	6.6%	84	7.9%	AS-	Stressful	1990-2011	SSA	No
5	Bagozzi et al. (2017)	The Journal of Politics	4.220	4	0.2%	0	0.0%	AS-	Stressful	1995-2008	World	No
6	Bai and Kung (2011)	The Review of Economics and Statistics	6.765	26	1.1%	0	0.0%	AS+; AS-	Pacifying; stressful	-220-1839	EAP	China
7	Berman and Couttenier (2015)	The Review of Economics and Statistics	5.133	246	10.0%	120	11.2%	AS+; other	Pacifying; stressful	1989-2005; 1989-2006; 1997-2006	SSA	No
8	Berman et al. (2017)	American Economic Review°	12.047	227	9.2%	130	12.2%	HS+	Stressful	1997-2010	SSA	No
9	Bhavnani and Lacina (2015)	World Politics	3.646	5	0.2%	4	0.4%	AS-	Stressful	1982-2000	South Asia	India
10	Bohlken and Sergenti (2010)	Journal of Peace Research#	2.272	2	0.1%	0	0.0%	AS+	Pacifying	1982-1995	South Asia	India
11	Bollfrass and Shaver (2015)	PLoS ONE	1.427	30	1.2%	0	0.0%	AS+; AS-; CS+; CS-	Uncertain	1989-2008	World	No
12	Buhaug et al. (2021)	The Journal of Politics	3.027	15	0.6%	12	1.1%	AS-	Stressful	1971-2013	World	No
13	Carreri and Dube (2017)	The Journal of Politics	4.220	4	0.2%	0	0.0%	HS+	Stressful	1997-2005	LAC	Colombia
14	Caruso et al. (2016)	Journal of Peace Research#	3.586	20	0.8%	0	0.0%	AS-	Stressful	1993-2003	EAP	Indonesia
15	Christensen (2019)	International Organization	7.363	21	0.9%	14	1.3%	HS+	Stressful	1997-2013	Africa	No
16	Christensen et al. (2019)	World Politics	2.861	5	0.2%	2	0.2%	HS+	Stressful	2006-2010; 2006-2015; 2011-2015	EAP	Myanmar
17	Corvalan and Pazzona (2019)	Journal of Economic Behavior and Organization	1.482	34	1.4%	0	0.0%	HS+	Pacifying	2003-2008; 2003-2013	LAC	Chile
18	Crost and Felter (2020)	Journal of the European Economic Association	7.792	118	4.8%	46	4.3%	AS+	Pacifying; stressful	2001-2009; 2003-2009	EAP	Philippines
19	Dagnelie et al. (2018)	Journal of Health Economics	3.106	80	3.2%	0	0.0%	HS+	Stressful	1997-2004	SSA	Congo, Dem. Rep.
20	De Juan (2015)	Political Geography	2.025	10	0.4%	0	0.0%	AS+; AS-	Pacifying; stressful	2003-2005	SSA	Southern Sudan (Darfur)
21	Detges (2016)	Journal of Peace Research#	3.586	10	0.4%	8	0.7%	AS-	Stressful	1990-2010	SSA	No
22	Döring (2020)	Political Geography	1.527	6	0.2%	0	0.0%	AS-	Stressful	1990-2014	World; SSA	No
23	Dube and Vargas (2013)	Review of Economic Studies°	12.200	55	2.2%	6	0.6%	AS+; HS+	Pacifying; stressful	1988-2004; 1988-2005	LAC	Colombia
24	Dube et al. (2016)	Journal of the European Economic Association	8.113	54	2.2%	0	0.0%	AS+	Pacifying	1990-2005; 1990-2010	LAC	Mexico
25	Eastin (2018)	Political Geography	1.659	12	0.5%	0	0.0%	AS-	Stressful	2001-2007	EAP	Philippines
26	Fetzer (2020)	Journal of the European Economic Association	7.792	43	1.7%	22	2.1%	AS+ ;AS-	Pacifying; stressful	2000-2010; 2000-2014	South Asia	India
27	Fjelde (2015)	World Development	2.253	12	0.5%	0	0.0%	AS+; AS-	Pacifying; stressful	1990-2010	Africa	No
28	Fjelde and Nilsson (2012)	Journal of Conflict Resolution#	3.448	12	0.5%	0	0.0%	HS+; other	Stressful	1987-2007	World	No
29	Fjelde and von Uexkull (2012)	Political Geography	2.137	15	0.6%	5	0.5%	AS+; AS-	Pacifying; stressful	1990-2008	SSA	No
30	Gong and Sullivan (2017)	Journal of African Economies	0.533	47	1.9%	0	0.0%	AS+; AS-	Pacifying; stressful	2002-2014	SSA	Uganda
31	Guardado (2018)	World Development	2.254	54	2.2%	49	4.6%	AS-	Stressful	1980-2000; 1988-2005	LAC	Colombia; Peru
32	Harari and Ferrara (2018)	The Review of Economics and Statistics	8.363	19	0.8%	5	0.5%	AS+	Pacifying	1997-2011	SSA	No

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Table 3 continued: Characteristics of Individual Studies

#	Study	Review	SJR score	Regressions		Interaction		Channel(s) of transmission	Mechanism(s)	Time period(s)	Region	Country focus
				#	% total	#	%					
33	Hidalgo et al. (2010)	The Review of Economics and Statistics	7.882	73	3.0%	56	5.2%	AS-; other	Stressful	1988-2004; 1991; 2000	LAC	Brazil
34	Hong and Yang (2020)	British Journal of Political Science°	4.116	48	1.9%	30	2.8%	HS+	Pacifying	1998-2005	EAP	China (Xinjiang)
35	Jia (2014)	The Economic Journal	5.264	182	7.4%	92	8.6%	AS-	Stressful	1470-1900	EAP	China
36	Kung and Ma (2014))	Journal of Development Economics	4.712	77	3.1%	32	3.0%	AS-	Stressful	1651-1910	EAP	China (Shandong)
37	Landis et al. (2017)	Political Geography	1.770	72	2.9%	72	6.7%	AS+; AS-	Pacifying; stressful	1997-2012	SSA	No
38	Lessmann and Steinkraus (2019)	European Journal of Political Economy	1.107	9	0.4%	4	0.4%	HS+	Stressful	2000-2012	World	No
39	Linke et al. (2015)	Global Environmental Change	3.504	10	0.4%	8	0.7%	AS+; AS-	Pacifying; stressful	2013	SSA	Kenya
40	Linke et al. (2018)	Journal of Conflict Resolution#	4.341	19	0.8%	16	1.5%	AS-	Stressful	2014	SSA	Kenya
41	Lujala (2010)	Journal of Peace Research#	2.272	14	0.6%	0	0.0%	HS+	Stressful	1946-2001	World	No
42	Maystadt and Ecker (2014)	American Journal of Agricultural Economics	1.521	2	0.1%	0	0.0%	AS-	Stressful	1997-2009	SSA	Somalia
43	Maystadt et al. (2014)	Oxford Economic Papers	0.687	20	0.8%	0	0.0%	HS+	Stressful	1997-2007	SSA	Congo, Dem. Rep.
44	Maystadt et al. (2015)	Journal of Economic Geography	2.957	49	2.0%	22	2.1%	AS-; CS+; CS-	Uncertain; Stressful	1997-2009	SSA	Southern Sudan (incl. future South Sudan)
45	McGuirk and Burke (2020)	Journal of Political Economy°	21.034	96	3.9%	53	5.0%	AS+; AS-	Pacifying; stressful	1989-2010; 1997-2013; 1999-2009	Africa	No
46	Nordkvelle et al. (2017)	Climatic Change	2.035	7	0.3%	0	0.0%	CS-	Uncertain	1989-2013	World	No
47	O'Loughlin et al. (2012)	Proceedings of the National Academy of Sciences (PNAS)	6.868	10	0.4%	0	0.0%	AS+; AS-	Pacifying; stressful	1991-2009	SSA	No
48	O'Loughlin et al. (2014)	Proceedings of the National Academy of Sciences (PNAS)	6.898	2	0.1%	0	0.0%	CS-	Uncertain	1980-2012	SSA	No
49	Papaioannou (2016)	Political Geography	2.098	2	0.1%	0	0.0%	AS-	Stressful	1912-1945	SSA	Nigeria
50	Papaioannou (2017)	European Review of Economic History	0.702	33	1.3%	12	1.1%	AS-	Stressful	1910-1939	World	No
51	Papaioannou and de Haas (2017)	World Development	2.122	93	3.8%	18	1.7%	AS-	Stressful	1920-1939	SSA (former British colonial area)	No
52	Raleigh and Kniveton (2012)	Journal of Peace Research#	2.985	16	0.6%	0	0.0%	CS+: CS-	Uncertain	1997-2009	SSA	No
53	Raleigh et al. (2015)	Global Environmental Change	3.504	8	0.3%	0	0.0%	AS+; AS-	Pacifying; stressful	1997-2010	SSA	No
54	Rigterink (2020)	Journal of Conflict Resolution#	2.671	32	1.3%	32	3.0%	HS+	Stressful	2004-2015	Africa	No
55	Rowhani et al. (2011)	Climatic Change	1.532	2	0.1%	0	0.0%	AS+	Pacifying	2005-2010	SSA	No
56	Sarsons (2015)	Journal of Development Economics	3.100	63	2.6%	35	3.3%	AS+	Pacifying	1970-1995	South Asia	India
57	Shapiro and Vanden Eynde (2023)*	The Review of Economics and Statistics	8.245	6	0.2%	0	0.0%	HS+	Stressful	2007-2011	South Asia	India (Red corridor)
58	Theisen (2012)	Journal of Peace Research#	2.985	16	0.6%	0	0.0%	AS+; AS-	Pacifying; stressful	1989-2004	SSA	Kenya
59	Theisen et al. (2012)	International Security#	4.318	3	0.1%	2	0.2%	AS-	Stressful	1960-2004	Africa	No
60	Vanden Eynde (2018)	Economic Journal	5.009	63	2.6%	54	5.1%	AS-	Stressful	2005-2011	South Asia	India
61	Wischnath and Buhaug (2014)	Climatic Change	2.440	11	0.4%	0	0.0%	CS+; CS-	Uncertain	1951-2008	World	No
62	Witmer et al. (2017)	Journal of Peace Research#	3.888	2	0.1%	0	0.0%	CS-	Uncertain	1980-2012	SSA	No
63	Yeeles (2015)	Journal of Peace Research#	3.892	24	1.0%	0	0.0%	CS+; CS-	Uncertain	1960-2006	World	No
64	von Uexkull (2014)	Political Geography	2.815	16	0.6%	12	1.1%	AS-	Stressful	1989-2008	SSA	No

Notes: *: published online in 2021 on peer-review journal website, but attributed to a journal issue in 2023. #: conflict specialized peer-review journal. °: top five peer-review journal in Economics or Political Science. SJR scores are established for the year of the publication. AS+: positive agricultural shock. AS-: negative agricultural shock. HS+: positive hydrocarbon shock. CS+ (CS-): positive (negative) pure climatic shock with no explicit impact through agriculture. Other: other potential detrimental shocks (positive drug shock; negative financial shock; negative labor market shock). EAP: East Asia & Pacific (World Bank definition). LAC: Latin America & the Caribbean (World Bank definition). SSA: Sub-Saharan Africa (World Bank definition). Except for Africa (Sub-Saharan Africa and North Africa), we consider a worldwide sample if two or more developing regions included in a given regression. For a detailed description of transmission channels, see Tables 4, 5, 6, and 7. For a detailed description of mechanisms, see Tables 8 and 9. For a detailed description of interactive terms, see Table 10. *Source: Authors' compilation from MRA database.*

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Table 4: Details of Transmission Channels [Positive Agricultural Shocks, AS+]

Study	Sub-component	Type	# Regressions	% transmission channel
Abidoye and Cali (2021)	Prices of produced commodities	Price	11	1.5%
Acharya et al. (2020)	Exports (log) instrumented by Hajj months; international lamb price change; local sheep and goat price change	Price; other	10	1.4%
Ahrens (2015)	Growth instrumented by temperature	Climate	4	0.6%
Bai and Kai-sing (2011)	Share of years with records of levee breaches of Yellow River in a given decade	Climate	13	1.8%
Berman and Couttenier (2015)	(Positive) agricultural demand shock	Other	201	28.3%
Bohlken and Sergenti (2010)	Growth instrumented by rainfalls	Climate	2	0.3%
Bollfrass and Shaver (2015)	Precipitation	Climate	5	0.7%
Crost and Felter (2020)	Several crops*price (mainly cavendish bananas)	Climate; price	118	16.6%
De Juan (2015)	Normalized Difference Vegetation Index (NDVI) 1998-2002	Climate	8	1.1%
Dube and Vargas (2013)	Coffee intensity*price	Price	20	2.8%
Dube et al. (2016)	Agro-climatically attainable yield for maize *national maize price in year (instrumented by lagged weather conditions)	Climate; price	54	7.6%
Fetzer (2020)	NREGA social program	Other	9	1.3%
Fjelde (2015)	Spatial data on crop production*international prices	Price	11	1.5%
Fjelde and Uexkull (2012)	Inter-annual positive rainfall anomaly	Climate	1	0.1%
Gong and Sullivan (2017)	Several crops*price (mainly coffee)	Price	44	6.2%
Harari and La Ferrara (2018)	Standardized Precipitation-Evapotranspiration Index (SPEI)*Growing Season, t-1	Climate	19	2.7%
Landis et al. (2017)	Precipitation trend	Climate	36	5.1%
Linke et al. (2015)	Changes in Vegetation conditions (VCI)	Climate	2	0.3%
McGuirk and Burke (2020)	Producer price index: price*crop share land	Price	68	9.6%
O'Loughlin et al. (2012)	Precipitation (SPI6); Precipitation (wet)	Climate	4	0.6%
Raleigh et al. (2015)	Positive rainfalls lagged 1yr	Climate	1	0.1%
Rowhani et al. (2011)	iEVI (ecosystem productivity: total annual vegetation activity)	Climate	2	0.3%
Sarsons (2015)	Rain growth; rain shock	Climate	63	8.9%
Theisen (2012)	Distance to Drought (SPI6)	Climate	4	0.6%
Total			710	100%

Notes: For a data visualization of subcomponents of transmission channels, see Figure A1 and Table A1 in the Appendix. *Source: Authors' compilation from MRA database.*

Table 5: Details of Transmission Channels [Negative Agricultural Shocks, AS-]

Study	Sub-component	Type	# Regressions	% transmission channel
Abidoye and Cali (2021)	Prices of consumed commodities	Price	11	1.0%
Almer et al. (2017)	Standardized Precipitation-Evapotranspiration Index (SPEI)	Climate	162	15.4%
Bagozzi et al. (2017)	Drought	Climate	4	0.4%
Bai and Kai-sing (2011)	Share of years with records of drought disasters on the central plains in a given decade	Climate	13	1.2%
Bhavnani and Lacina (2015)	Internal migration instrumented by abnormal rainfall (Monsoon)	Climate	5	0.5%
Bollfrass and Shaver (2015)	Temperature	Climate	5	0.5%
Buhaug et al. (2021)	Drought (SPEI)	Climate	15	1.4%
Caruso et al. (2016)	Paddy rice production instrumented by temperature deviation	Climate	20	1.9%
De Juan (2015)	Normalized Difference Vegetation Index (NDVI) 1998-2002	Climate	2	0.2%
Detges (2016)	Extreme drought	Climate	10	1.0%
Doring (2020)	Several measures on groundwater scarcity	Climate	6	0.6%
Eastin (2018)	Typhoon last year	Climate	12	1.1%
Fetzer (2020)	Log(Monsoon t-1)	Climate	34	3.2%
Fjelde (2015)	Spatial data on crop production*international prices	Price	1	0.1%
Fjelde and Uexkull (2012)	Inter-annual negative rainfall anomaly	Climate	14	1.3%
Gong and Sullivan (2017)	Coffee intensity*price (-1 standard deviation)	Price	3	0.3%
Guardao (2018)	Coffee intensity*price; agro-climatic attainable yield for coffee*price	Climate; price	54	5.1%
Hidalgo et al. (2010)	Agricultural income instrumented by rain deviation; rainfall deviation	Climate	72	6.9%
Jia (2014)	Several measures on droughts and floods	Climate	182	17.3%
Kun and Ma (2014)	Crop failure; Drought; Flood	Climate; other	77	7.3%
Landis et al. (2017)	Negative precipitation variability	Climate	36	3.4%
Linke et al. (2015)	Drought (SAT and TAMSAT)	Climate	8	0.8%
Linke et al. (2018)	Drought (SAT and TAMSAT)	Climate	19	1.8%
Maystadt and Ecker (2014)	Drought length (in months); cattle price (log) instrumented by drought length (in month)	Climate	2	0.2%
Maystadt et al. (2015)	Precipitation anomaly; Temperature anomaly	Climate	19	1.8%
McGuirk and Burke (2020)	Consumer price index: price*crop share land	Price	28	2.7%
O'Loughlin et al. (2012)	Precipitation (dry); several measures of temperature	Climate	6	0.6%
Papaioannou (2016)	Rainfall deviation square	Climate	2	0.2%
Papaioannou (2017)	Several measure on rainfall deviations/shocks	Climate	33	3.1%
Papaioannou and De Haas (2017)	Several measure on rainfall deviations/shocks	Climate	93	8.9%
Raleigh et al. (2015)	Several measures of commodity prices instrumented by negative shocks; Negative rainfalls	Climate; price	7	0.7%
Theisen (2012)	Drought (SPI6); Rainfall defficiency (SPI6); Temperature (SPI6)	Climate	12	1.1%
Theisen et al. (2012)	Drougt (SPI)	Climate	3	0.3%
Vanden Eynde (2018)	Rain deficiency t-1	Climate	63	6.0%
von Uexkull (2014)	Several measure of drought	Climate	16	1.5%
Total			1049	100%

Notes: For a data visualization of subcomponents of transmission channels, see Figure A1 and Table A1 in the Appendix. *Source: Authors' compilation from MRA database.*

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Table 6: Details of Transmission Channels [Positive Hydrocarbon and Mineral Shocks, HS+]

Study	Sub-component	Type	# Regressions	% transmission channel
Berman et al. (2017)	Mines*prices	Price	227	41.8%
Carreri and Dube (2017)	Municipality that produced oil in 1993*oil price	Price	4	0.7%
Christensen (2019)	Active mine*price	Price	21	3.9%
Christensen et al. (2019)	Active mine*price	Price	5	0.9%
Corvalan and Pazzona (2019)	Production copper in 2000*prices	Price	34	6.3%
Dagnelie et al. (2018)	Weighted minerals endowment*price for each mineral (several minerals)	Price	80	14.7%
Dube and Vargas (2013)	Coal prod*coal price; gold prod*gold price; oil prod*oil price	Price	35	6.4%
Fjelde and Nilsson (2012)	Presence of gemstones in conflict area; presence of oil/gas in conflict area	Other	8	1.5%
Hong and Yang (2018)	Several measures based on gas and oil prices and gas and oil revenue	Price; other	48	8.8%
Lessmann and Steinkraus (2019)	Mineral Gini as concentration of mine light across ethnicities	Other	9	1.7%
Lujala (2010)	Mineral and hydrocarbon production/reserves in conflict zone	Other	14	2.6%
Maystadt et al. (2014)	Subsidies to mining concessions	Price	20	3.7%
Rigterink (2020)	Diamond propensity*price; diamond propensity*price (price instrumented with Russian prod. volume)	Price	32	5.9%
Shapiro and Vanden Eynde (2021)	Iron deposits*post new royalty regime	Other	6	1.1%
Total			543	100%

Notes: For a data visualization of subcomponents of transmission channels, see Figure A1 and Table A1 in the Appendix.
Source: Authors' compilation from MRA database.

Table 7: Details of Transmission Channels [Other Shocks]

Study	Sub-component	Type	# Regressions	% transmission channel
Pure negative climatic shocks (Other 1)				
Bollfrass and Shaver (2015)	Precipitation; Temperature	Climate	18	23.4%
Maystadt et al. (2015)	Precipitation anomaly; Temperature anomaly	Climate	21	27.3%
Nordkvelle et al. (2017)	Absolute SPI; Drought; Flood	Climate	7	9.1%
O'Loughlin et al. (2014)	Precipitation (SPI6); Temperature (SPI6)	Climate	2	2.6%
Raleigh and Kniveton (2012)	Rainfall variation	Climate	8	10.4%
Wischnath and Buhaug (2014)	Drought; precipitation deviation, growth and level	Climate	6	7.8%
Witmer et al. (2017)	Precipitation (SPI6); Temperature (SPI6)	Climate	2	2.6%
Yeeles (2015)	Precipitation; Temperature	Climate	13	16.9%
Total			77	100%
Other potential detrimental shocks (Other 2)				
Berman and Couttenier (2015)	(Negative) financial crises shock	Other	45	90.0%
Fjelde and Nilsson (2012)	Presence of drugs in conflict area	Other	4	8.0%
Hidalgo et al. (2010)	Log rural unemployment instrumented by rain deviation	Climate	1	2.0%
Total			50	100%
Pure positive climatic shocks (Other 3)				
Bollfrass and Shaver (2015)	Precipitation	Climate	2	5.7%
Maystadt et al. (2015)	Precipitation anomaly; Temperature anomaly	Climate	9	25.7%
Raleigh and Kniveton (2012)	Rainfall variation	Climate	8	22.9%
Wischnath and Buhaug (2014)	Temperature deviation, growth and level	Climate	5	14.3%
Yeeles (2015)	Precipitation; Temperature	Climate	11	31.4%
Total			35	100%

Notes: For a data visualization of subcomponents of transmission channels, see Figure A1 and Table A1 in the Appendix.
Source: Authors' compilation from MRA database.

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Table 8: Details of Stressful Mechanisms

Study	Sub-component	# Regressions	% transmission channel
Abidoye and Cali (2021)	Enhanced poverty (budget constraint)	11	0.6%
Almer et al. (2017)	Enhanced poverty (water insecurity)	162	9.5%
Bagozzi et al. (2017)	Enhanced poverty (food scarcity)	4	0.2%
Bai and Kai-sing (2011)	Enhanced poverty (food scarcity)	13	0.8%
Berman and Couttenier (2015)	Enhanced poverty (budget constraint)	45	2.7%
Berman et al. (2017)	Feasability for insurgents to fund their activity	227	13.4%
Bhavnani and Lacina (2015)	Exodus	5	0.3%
Buhaug et al. (2021)	Enhanced poverty (lack dynamism of local economy)	15	0.9%
Carreri and Dube (2017)	Rent capture	4	0.2%
Caruso et al. (2016)	Enhanced poverty (food scarcity)	20	1.2%
Christensen (2019)	Imperfect information (lack transparency extractive dividend)	21	1.2%
Christensen et al. (2019)	Imperfect information (lack transparency extractive dividend)	5	0.3%
Crost and Felter (2020)	Rent capture	102	6.0%
Dagnelie et al. (2018)	Rent capture	80	4.7%
De Juan (2015)	Rent capture (livestock and vegetation for pastoral population)	8	0.5%
Detges (2016)	Enhanced poverty (food scarcity)	10	0.6%
Doring (2020)	Enhanced poverty (water insecurity)	6	0.4%
Dube and Vargas (2013)	Rent capture	35	2.1%
Eastin (2018)	Regional destruction (including agricultural soil)	12	0.7%
Fetzer (2020)	Enhanced poverty (budget constraint; food scarcity)	34	2.0%
Fjelde (2015)	Enhanced poverty (budget constraint)	1	0.1%
Fjelde and Nilsson (2012)	Rent capture	12	0.7%
Fjelde and Uexkull (2012)	Enhanced poverty (water insecurity)	14	0.8%
Gong and Sullivan (2017)	Rent capture	41	2.4%
Guardao (2018)	Enhanced poverty (budget constraint)	54	3.2%
Hidalgo et al. (2010)	Enhanced poverty (budget constraint)	73	4.3%
Jia (2014)	Enhanced poverty (food scarcity)	182	10.7%
Kun and Ma (2014)	Enhanced poverty (food scarcity)	77	4.5%
Landis et al. (2017)	Enhanced poverty (water insecurity)	36	2.1%
Lessmann and Steinkraus (2019)	Grievance	9	0.5%
Linke et al. (2015)	Grievance	8	0.5%
Linke et al. (2018)	Grievance	19	1.1%
Lujala (2010)	Rent capture	14	0.8%
Maystadt and Ecker (2014)	Enhanced poverty (budget constraint)	2	0.1%
Maystadt et al. (2014)	Rent capture	20	1.2%
Maystadt et al. (2015)	Enhanced poverty (food scarcity; water insecurity)	15	0.9%
McGuirk and Burke (2020)	Enhanced poverty (budget constraint)	28	1.6%
O'Loughlin et al. (2012)	Enhanced poverty (food scarcity)	6	0.4%
Papaioannou (2016)	Regional destruction (including agricultural soil)	2	0.1%
Papaioannou (2017)	Enhanced poverty (food scarcity)	33	1.9%
Papaioannou and De Haas (2017)	Regional destruction (including agricultural soil)	93	5.5%
Raleigh et al. (2015)	Enhanced poverty (budget constraint)	7	0.4%
Rigterink (2020)	Rent capture	32	1.9%
Shapiro and Vanden Eynde (2021)	Rent capture; state capacity (security operations)	6	0.4%
Theisen (2012)	Enhanced poverty (food scarcity)	12	0.7%
Theisen et al. (2012)	Enhanced poverty (food scarcity)	3	0.2%
Vanden Eynde (2018)	Enhanced poverty (budget constraint)	63	3.7%
von Uexkull (2014)	Enhanced poverty (food scarcity)	16	0.9%
Total		1,697	100%

Source: Authors' compilation from MRA database.

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Table 9: Details of Pacifying and Uncertain Mechanisms

Study	Sub-component	# Regressions	% transmission channel
Pacifying mechanisms			
Abidoye and Cali (2021)	Reduced poverty (budget constraint)	11	1.7%
Acharya et al. (2020)	Reduced poverty (budget constraint)	10	1.6%
Ahrens (2015)	Reduced poverty (dyn. of local economy)	4	0.6%
Bai and Kai-sing (2011)	Reduced poverty (food scarcity)	13	2.0%
Berman and Couttenier (2015)	Reduced poverty (budget constraint)	201	31.4%
Bohlken and Sergenti (2010)	Reduced poverty (dyn. of local economy)	2	0.3%
Corvalan and Pazzona (2019)	Reduced poverty (dyn. of local economy)	34	5.3%
Crost and Felter (2020)	Reduced poverty (budget constraint; food scarcity)	16	2.5%
De Juan (2015)	Lower incentive for rent capture (livestock and vegetation pastoral pop.)	2	0.3%
Dube and Vargas (2013)	Reduced poverty (budget constraint)	20	3.1%
Dube et al. (2016)	Reduced poverty (budget constraint)	54	8.4%
Fetzer (2020)	Reduced poverty (budget constraint; food scarcity)	9	1.4%
Fjelde (2015)	Reduced poverty (budget constraint)	11	1.7%
Fjelde and Uexkull (2012)	Reduced poverty (water insecurity)	1	0.2%
Gong and Sullivan (2017)	Reduced poverty (food scarcity); Lower rent capture	6	0.9%
Harari and La Ferrara (2018)	Reduced poverty (food scarcity)	19	3.0%
Hong and Yang (2018)	Reduced poverty (budget constraint; water scarcity)	48	7.5%
Landis et al. (2017)	Reduced poverty (water insecurity)	36	5.6%
Linke et al. (2015)	Lower grievance	2	0.3%
McGuirk and Burke (2020)	Reduced poverty (budget constraint)	68	10.6%
O'Loughlin et al. (2012)	Reduced poverty (food scarcity)	4	0.6%
Raleigh et al. (2015)	Reduced poverty (budget constraint)	1	0.2%
Rowhani et al. (2011)	Lower grievance or reverse causality	2	0.3%
Sarsons (2015)	Reduced poverty (budget constraint)	63	9.8%
Theisen (2012)	Reduced poverty (food scarcity)	4	0.6%
Total		641	100%
Uncertain mechanisms			
Bollfrass and Shaver (2015)	None specifically	30	23.8%
Maystadt et al. (2015)	None specifically	34	27.0%
Nordkvelle et al. (2017)	None specifically	7	5.6%
O'Loughlin et al. (2014)	None specifically	2	1.6%
Raleigh and Kniveton (2012)	None specifically	16	12.7%
Wischnath and Buhaug (2014)	None specifically	11	8.7%
Witmer et al. (2017)	None specifically	2	1.6%
Yeeles (2015)	None specifically	24	19.0%
Total		126	100%

Source: Authors' compilation from MRA database.

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Table 10: Details of interaction terms

#	Study	Subgroup	Risk absorber	Risk enhancer	Risk undetermined
1	Abidoye and Cali (2021)	AS+/-	-	-	-
2	Acharya et al. (2020)	AS+	Institutional framework in Somaliland	Institutional framework in Puntland	-
3	Ahrens (2015)	AS+	-	-	-
4	Almer et al. (2017)	AS-	Several including high blue water per capita; high distance to urban center; no ethnic diversity	Several including low blue water per capita; low distance to urban center; ethnic diversity	-
5	Bagozzi et al. (2017)	AS+	-	-	-
6	Bai and Kung (2011)	AS+/-	-	-	-
7	Berman and Couttenier (2015)	AS+, other	Low distance to seaport; local revenue mobilization	Distance to seaport; distance to natural resources	Various measures
8	Berman et al. (2017)	HS+	Several including relatively higher governance indicators; proxy of lack rent incentives	Several including ethnic and religious fract./polarization; Gini index; mineral rents	Mines characteristics
9	Bhavnani and Lacina (2015)	AS-	Low unemployment in host state; political match between migrant and host state	High unemployment in host state; political mismatch between migrant and host state	-
10	Bohlken and Sergenti (2010)	AS+	-	-	-
11	Bollfrass and Shaver (2015)	AS+/-, other	-	-	-
12	Buhaug et al. (2021)	AS-	-	Several terms based on discriminated and downgraded groups	-
13	Carreri and Dube (2017)	HS+	-	-	-
14	Caruso et al. (2016)	AS-	-	-	-
15	Christensen (2019)	HS+	WGI control of corruption; EITI* candidate; EITI* compliant member	Mineral price	-
16	Christensen et al. (2019)	HS+	Post-2000 (democratization)	Mineral price	-
17	Corvalan and Pazzona (2019)	HS+	-	-	-
18	Crost and Felter (2020)	AS+	-	Several terms based on resource endowment, muslim pop., territories control by rebel groups	-
19	Dagnelie et al. (2018)	HS+	-	-	-
20	De Juan (2015)	AS+/-	-	-	-
21	Detges (2016)	AS-	Relatively good access to alternative water sources; relatively high density paved roads	Low density paved roads	-
22	Doring (2020)	AS-	-	-	-
23	Dube and Vargas (2013)	AS+, HS+	-	Years with pro-para majority local councils	-
24	Dube et al. (2016)	AS+	-	-	-
25	Eastin (2018)	AS-	-	-	-
26	Fetzer (2020)	AS+	Several measures based on NREGA** social program; outside red corridor	Inside red corridor	-
27	Fjelde (2015)	AS+/-	-	-	-
28	Fjelde and Nilsson (2012)	HS+, other	-	-	-
29	Fjelde and Uexkull (2012)	AS/-	-	-	Various measures
30	Gong and Sullivan (2017)	AS+/-	-	-	-
31	Guardao (2018)	AS-	Several measures based on shared arrangement on lands	Agricultural price	-
32	Harari and La Ferrara (2018)	AS+	-	-	Various measures based on groups and infrastructures
33	Hidalgo et al. (2010)	AS+/-, other	Several measures based on low land Gini	Several measures based on land Gini	Mainly contracts characteristics
34	Hong and Yang (2018)	HS+	Several measures based on gas and oil prices and gas and oil revenue	Mosque density in Xinjiang	-
35	Jia (2014)	AS-	Mainly the practice of culture of sweet potatoes	Mainly the lack of culture of sweet potatoes	Time trend
36	Kung and Ma (2014)	AS-	Several proxies of Confucean culture (#chaste women per area; #temples; #sages)	-	-
37	Landis et al. (2017)	AS+/-	Shared ethnicity; higher road density	The distance to Niger river	-
38	Lessmann and Steinkraus (2019)	HS+	Higher institutional quality; low inequality in mineral districts	Higher inequality in mineral distribution	-
39	Linke et al. (2015)	AS+/-	Presence of rules to manage resources and conflicts on resources	No rule to manage resources	-
40	Linke et al. (2018)	AS-	Presence of rules to manage resources and conflicts on resources	No rule to manage resources	-
41	Lujala (2010)	HS+	-	-	-
42	Maystadt and Ecker (2014)	AS-	-	-	-
43	Maystadt et al. (2014)	HS+	-	-	-
44	Maystadt et al. (2015)	AS-, other	Several measures based on favorable agricultural potential	Several measures based on unfavorable agricultural potential	-
45	McGuirk and Burke (2020)	AS+/-	Cash crops; high luminosity as proxy of urban activity	Food crops; low luminosity as proxy of urban activity	-
46	Nordkvelle et al. (2017)	other	-	-	-
47	O'Loughlin et al. (2012)	AS+/-	-	-	-
48	O'Loughlin et al. (2014)	other	-	-	-
49	Papaioannou (2016)	AS-	-	Several measures based on unfavorable agricultural potential	-
50	Papaioannou (2017)	AS-	Several measures based on favorable agricultural potential	Exceptional drought; exceptional flood	-
51	Papaioannou and De Haas (2017)	AS-	Export crop production and suitability	-	-
52	Raleigh and Kniveton (2012)	other	-	-	-
53	Raleigh et al. (2015)	AS+/-	-	-	-
54	Rigterink (2020)	HS+	Off-archon kimberlite; primary diamond	Secondary diamond; Upstream rivers diamond	-
55	Rowhani et al. (2011)	AS+	-	-	-
56	Sarsons (2015)	AS+	Presence of district dam downstream	No district dam downstream	Several measures based on slopes and soil elevation
57	Shapiro and Vanden Eynde (2021)	HS+	-	-	-
58	Theisen (2012)	AS+/-	-	-	-
59	Theisen et al. (2012)	AS-	No of marginalized ethnic groups	Presence of marginalized ethnic groups	-
60	Vanden Eynde (2018)	AS-	-	Agricultural share for neighbours; external source of revenues for locals	Agricultural share for locals; various measures based on the lack of mining neighbours
61	Wischnath and Buhaug (2014)	other	-	-	-
62	Witmer et al. (2017)	other	-	-	-
63	Yeeles (2015)	other	-	-	-
64	von Uexkull (2014)	AS-	No rainfed croplands	Rainfed croplands	-

Notes: *: EITI stands for Extractives Industries Transparency Initiative.**: National Rural Employment Guarantee Act.
Source: Authors' compilation from MRA database.

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4 Studies' Collection Strategy and Inclusion Criteria

To identify relevant studies for our meta-analysis, we utilized three research methods. First, we employed reference snowballing techniques on two seminal conflict literature reviews: Couttenier and Soubeyran (2015) and Theisen (2012). Second, we collected references from three meta-analyses on related topics: Blair et al. (2021), Vesco et al. (2020), and Hsiang et al. (2013, 2014). Third, we conducted keyword searches on Google Scholar and used web scraping via the R package 'rvest' (Wickham, 2022). We searched for keyword associations, such as [*"keyword1 shocks and keyword2"*] (in whole documents) and [*"keyword1 shocks" keyword2*] (in titles), where *keyword1* represents the type of shock - 'income', 'price', 'natural resource', 'climate', 'climatic' or 'environmental' - and *keyword2* represents the type of conflict outcome - 'conflict', 'war', 'violence', 'unrest'. We searched for singular and plural forms of keywords and searched 112 different keyword associations in August and September 2022. Figure 4 summarizes the process of identification, screening and inclusion of studies in our meta-sample.

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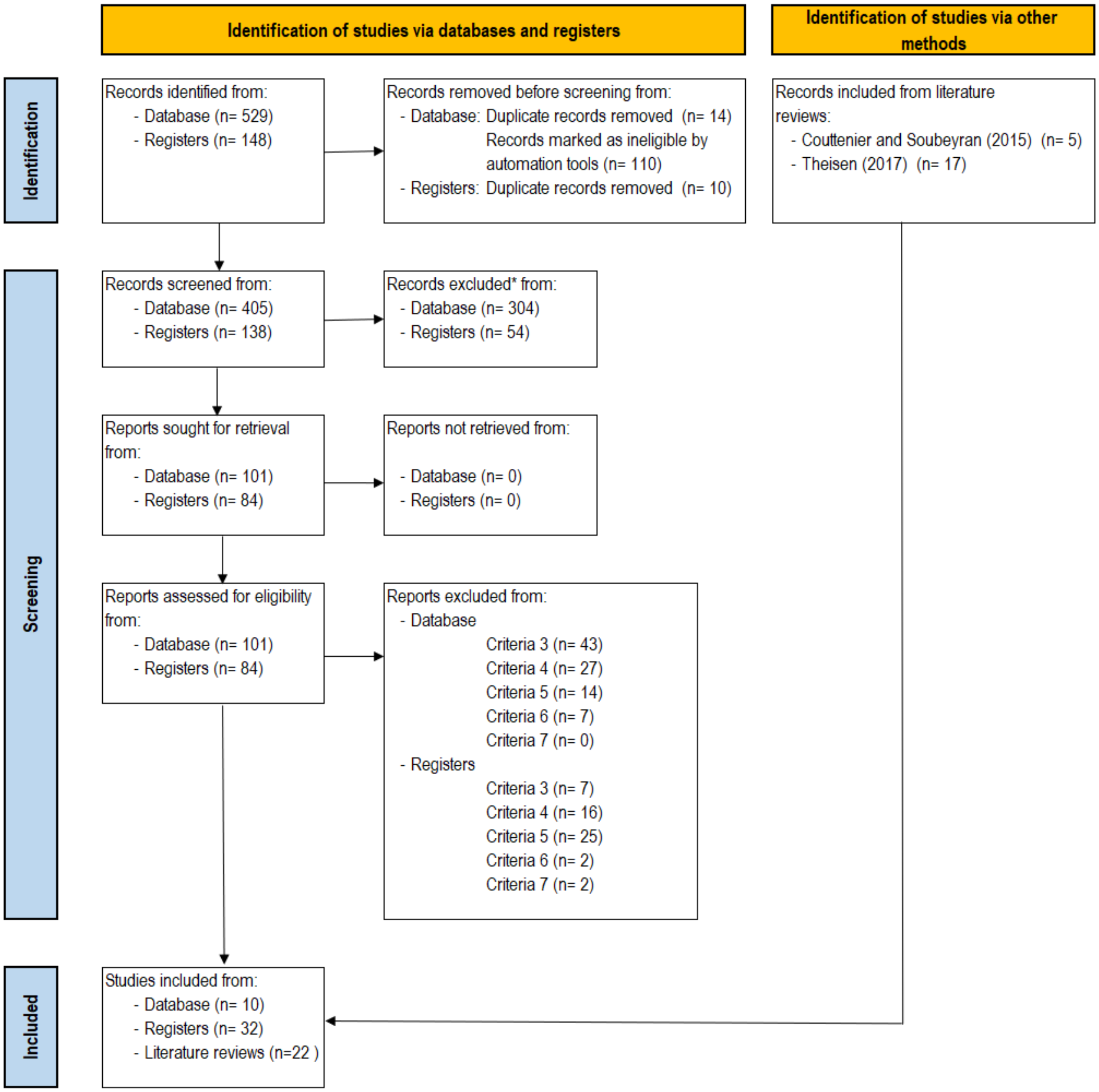

Notes: This Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) diagram shows the data collection flow of the meta-analysis. *: Excluded records do not meet the Inclusion Criteria (IC) 1 (to be published in a peer-reviewed journal) and/or the IC 2 (to be published between 2010 and 2021). The inclusion criteria (IC) 3 is to present exploitable empirical results (including standard errors or Student's t); IC 4 is to have a conflict output; IC 5 is to use a sub-national scale of analysis; IC 6 is to examine an income-related channel of transmission; IC 7 is to analyze non OECD's High incomes countries. Records are marked as ineligible by automation tools if they are citations or duplicates. *Source: Authors' compilation based on Page et al. (2021). For more information, visit:* `http://www.prisma-statement.org/`.

Figure 4: PRISMA 2020 Flow Diagram

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