## Feeding conflict? New data on the impact of humanitarian food aid on civil conflict

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November, 2024

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#### Abstract

Anecdotal and empirical evidence suggests a link between humanitarian food aid and violent conflict, but recent empirical research produced mixed results. This research note reconciles disparate findings by showing that previous measures of humanitarian food aid (1) fail to account for differences in within-country transportation costs and (2) conflate humanitarian and non-humanitarian food aid. I introduce a new dataset of USAID humanitarian food assistance across 103 countries between 1991 and 2019 which resolves these problems. I exclude shipping costs by using tonnage of food commodities and isolate the humanitarian portions of USAID's food assistance. I find a series of tightly estimated null relationships between humanitarian food aid and the incidence of conflict, conflict termination, and the duration of peace. These results do not change when I use these new data to measure the ease of appropriating humanitarian aid. By introducing new program-level data, this research note provides evidence on a disputed linkage and advances the literature on the unintended consequences of humanitarian assistance.

Keywords: conflict processes, humanitarian aid, civil war, new data, methodology

In 2019, Houthi rebels diverted food aid, blocked convoys, and interfered with the distribution of humanitarian food aid in Yemen. In response, the World Food Programme (WFP) threatened to cease its operations in the country (Michael 2020). Academic research has generalized such anecdotes. Scholars have variously argued that humanitarian food aid makes conflict more likely (Narang 2014; 2015; Nunn and Qian 2014); makes conflict less likely (Mary and Mishra 2020), has no effect on conflict (Christian and Barrett 2017).

This research note reconciles these disparate findings by identifying two challenges in previous measures of humanitarian aid flows. First, humanitarian aid disbursements, often sourced from the Organization for Economic Cooperation and Development (OECD), include in-country transportation costs. These costs are higher for mountainous, forested, and larger countries, which means that disbursements do not consistently map to the amount of aid delivered. Second, a significant portion of the US Agency for International Development (USAID)'s food aid portfolio comprised longer-term development projects, or in-kind assistance which is monetized by host governments to fund other projects. In other words, these projects appear as humanitarian food aid in the OCED data, but no food is received by beneficiaries on the ground.

This research note introduces project-level data on food assistance programs from USAID—the largest provider of humanitarian food aid in the world.<sup>1</sup> I digitized 29 years of USAID's *International Food Assistance Reports* (IFARs) which are congressionally mandated summaries of all USAID food assistance programs. These granular data span all recipients of US food assistance from 1991 to 2019. To avoid the inconsistent relationship between reported disbursements and the amount of aid delivered, these data measure the tonnage of food aid shipped rather than value of food assistance programs. Second, these data include the intended use of food aid, which allows me to subset only to in-kind humanitarian food assistance. By increasing the granularity and precision with which humanitarian aid can be measured, the IFAR dataset broadens the scope of feasible empirical questions about unintended consequences of humanitarian

<sup>&</sup>lt;sup>1</sup>In 2019, USAID provided 51.6 percent of global emergency food aid disbursements according to the OECD.

food aid.

These measurement challenges explain the previously disparate results. Humanitarian food aid does not affect the incidence of civil conflict when food aid is measured more accurately and in closer accord with the theoretical mechanisms which underpin the hypothesized relationship.<sup>2</sup> While some recent articles raised methodological concerns about the food aid-civil conflict relationship (Christian and Barret 2024; Christian and Barrett 2017), I show here that the null findings are more robust, in the sense that a more theoretically appropriate measure which addresses these methodological issues provides tightly estimated null results. Re-estimating a number of previous research designs using my new data, I find no relationship between humanitarian food aid and conflict incidence or the risk of peace failing. I find only a weak relationship with war termination. I further leverage the new data to show that the relationship between food aid and civil conflict outcomes is not affected by the ease of appropriating the food aid.

#### 1 Humanitarian food aid and conflict

Anecdotes about stolen humanitarian aid supporting rebels are common. For example, Houthi rebels in Yemen stole food aid and "diverted it to front-line combat units or sold it for profit on the black market" (Michael 2020). An extensive empirical literature reinforces these anecdotes by arguing that humanitarian food aid drives conflict (Nunn and Qian 2014; Wood and Sullivan 2015).

Humanitarian food aid is distinct as a conflict resource because it is immediately lootable. Humanitarian aid projects provide food and other immediately useful goods:

<sup>&</sup>lt;sup>2</sup>Incidence is a binary indicator for whether conflict exists given country-year.

blankets, mosquito nets, tarps, nutritional supplements, etc.<sup>3</sup> Armed groups need such goods to continue fighting (Koren and Bagozzi 2017).

By providing lootable resources which are necessary to continue fighting, humanitarian assistance can help armed groups prolong conflicts.<sup>4</sup> Development aid is less easily lootable. Water access programs, for instance, often contract to firms based in the capital, who then deploy personnel and equipment to implementation areas. This funding structure minimizes the money to be appropriated in the implementation area; the goods, such as excavation equipment or pipes, require conversion into a conflict good. Valuable assets like an irrigation perimeter could be contested by armed groups, and development aid could also increase the duration of civil conflict by promoting rent-seeking behavior by armed groups (Findley et al. 2011). However, short term appropriation of development aid by violent actors is more difficult, and development aid is also less likely to be deployed to active conflict zones (Findley 2018: 368). Together, these differences mean that it is important to examine the effects of humanitarian aid, independent of other forms of development assistance.

Humanitarian assistance may also have an indirect effect on the bargaining range between armed groups and states. Humanitarian assistance tends to be targeted towards the territory of the losing side of conflict (Narang 2014), especially in peripheral conflicts. This dynamic induces a commitment problem: if humanitarian aid strengthens the weaker side, it has a greater incentive to renege on agreements negotiated before the

<sup>&</sup>lt;sup>3</sup>Food aid is a subset of humanitarian aid, but it is the primary component of most humanitarian aid efforts.

<sup>&</sup>lt;sup>4</sup>Other literature studies project-level effects of development aid on violence. These studies largely find a positive, albeit context dependent effect of development projects on conflict, due to armed groups' desire to be seen as the sole provider of public goods (Child 2019; De Juan 2019). Wood and Sullivan (2015) apply a similar logic to humanitarian aid.

provision of humanitarian aid. Moreover, providing foreign aid can increase uncertainty in bargaining between the state and the armed group (Narang 2014). Uncertainty complicates the peace process and prolongs the conflict. These mechanisms are less applicable to development aid. Improved irrigation in rebel-controlled areas, for example, could increase the amount of food available to rebels in the long term. But it is not clear that the perimeter would have an immediate effect on the bargaining range between the state and the rebel group. Moreover, development aid is less likely to be targeted towards the losing group, so it will not have same effect as humanitarian aid on the bargaining range.

To summarize, the prevailing mechanism for why foreign aid drives conflict—rebel groups looting resources to prolong the conflict—applies largely to humanitarian aid, not development aid. The direct and indirect effects suggest that humanitarian and nonhumanitarian food aid will have different effects on violent conflict, and so it is necessary to distinguish between them.

#### 2 Measuring humanitarian food aid

Existing research claims that humanitarian food aid increases (Nunn and Qian 2014), decreases (Mary and Mishra 2020), or has no effect on (Christian and Barret 2024; Christian and Barrett 2017) conflict. Another set of literature claims that humanitarian food aid makes peace agreements more likely to fail (Narang 2014) or prolongs wars (Narang 2015). These studies vary across a variety of dimensions, including their outcome variable, methodology, and data source.

Most of these papers use conflict incidence as their outcome variable (Christian and

Barrett 2017; Mary and Mishra 2020; Nunn and Qian 2014); the exceptions look at durations of peace (Narang 2014) and war (Narang 2015). Methodologies also vary. The papers which explore conflict incidence use instrumental variables strategies (described in greater detail below); the other papers use survival analysis to capture the effects of humanitarian food aid while attempting to control for as many exogenous variables as possible. In a review of this literature, Zürcher (2017) finds a preponderance of evidence that humanitarian food aid exacerbates civil war, but nevertheless disparate results remain.<sup>5</sup>

Previous research has taken measurement issues seriously, but when it comes to foreign aid, "measurement issues are pernicious, and they are not trivial" (Findley 2018: 377). This research note argues that measurement strategies, rather than research designs, which drive the differing results. The OECD's Development Assistance Committee (DAC) keeps the most commonly used records of foreign aid disbursements. Most studies of humanitarian food aid and violent conflict use these disbursement data (Mary and Mishra 2020; Narang 2014; 2015; Zürcher 2017); the standardization of reporting across donors allows cross-country analysis of aid flows with ease. A notable exception is Nunn and Qian (2014), who instrument US food aid using the previous year's wheat harvest. Christian and Barret (2017) also use these data, albeit with a view to critique Nunn and Qian's results. An alternative literature, enabled by AidData's geocoding of OECD and other development data, disaggregates aid by geographic area (Wood and Molfino 2016). Importantly, AidData's geocoded data on foreign aid also relies on

<sup>&</sup>lt;sup>5</sup>Narang (2014) and (2015) measure humanitarian aid generally, rather than humanitarian food aid specifically. However, other types of humanitarian food aid—medicine, shelter, etc.—also require transportation costs, so the measurement problems remain relevant.

OECD disbursements to measure humanitarian food aid. Two problems arise from measuring humanitarian food aid through OECD disbursements which explain the disparate results.

The first problem with OECD disbursement data is that they do not distinguish between categories of food aid. Within US food assistance programs, tonnage figures can obfuscate significant differences in how food commodities will be used. Public Law 480, colloquially known as the Food for Peace Act, sets the framework for US food aid programs.<sup>6</sup> Multiple modalities within this legislation create significant heterogeneity within US food aid.<sup>7</sup> Title I and Title II food aid together comprise the bulk of U.S. food assistance. Title I food aid is a concessional loan program, by which developing countries received favorable credit terms for transfers of food commodities. These commodities can then be monetized by the recipient governments. Congress has not appropriated funds for Title I food aid since 2006.

Title II food aid transfers food commodities to non-governmental organizations. Title II food aid can be broken down into two further categories. Title II non-emergency (i.e. development) food aid supports multi-year projects to address causes of food insecurity. Title II development projects transfer these food commodities to implementing partners, commonly INGOs like the WFP or Save the Children, which then monetize the commodities to fund development projects. Finally, Title II emergency assistance provides food commodities to implementing partners, which then distribute in-kind food

<sup>&</sup>lt;sup>6</sup>During the period of study, US food assistance was administered and distributed by the Bureau of Food for Peace at USAID. As of 2020, FFP was merged with the Office of Foreign Disaster Assistance into the Bureau for Humanitarian Assistance.

<sup>&</sup>lt;sup>7</sup>Modality is commonly used within the humanitarian food aid literature to distinguish between in-kind food aid versus cash assistance; here I use the term to distinguish between the multiple types of in-kind food assistance.

assistance to local beneficiaries. Only Title II emergency (i.e. humanitarian) assistance is the humanitarian food aid commonly described in the food aid and violent conflict literature, where individuals in need receive bags of food stamped "from the American people." OECD disbursement data do not distinguish between these types of food aid.

The second problem with using OECD disbursement data is that the internal shipping costs mean that similar disbursements correspond to different amounts of food aid delivered. In fiscal year 2019, only 30 percent of USAID's funds used under the Title II food assistance program went to the purchase of commodities. An additional II percent of these funds were used to ship commodities from the United States to a port of entry, 4 percent to ship commodities inland from a port of entry, and 15 percent to cover administrative expenses. Another 25 percent of the funds went to "[c]osts directly associated with the transportation and distribution of commodities for the duration of a program, including storage, warehousing, and commodity-distribution costs; internal transport via rail, truck, or barge; commodity-monitoring in storage and at distribution sites; procuring vehicles; in-country operational expenses; and others."8 USAID categorizes the costs as Internal Shipping and Handling (ITSH). ITSH costs are not uniform across countries. The geography of some countries complicates food distribution. In the Democratic Republic of the Congo, long distances and rough terrain increases transportation costs. Humanitarian food aid to countries such as Somalia-which in 2019 received 84,520 metric tons of humanitarian food aid from USAID-presents no such geographic obstacles.

Table I shows average ITSH cost per ton for different subgroups of Title II programs.

<sup>&</sup>lt;sup>8</sup>These statistics come from pages 15-16 of the 2019 IFAR report; the report characterizes the remaining funds as 'other.'

	Mean Dollars per Ton
Presence of conflict	
Peace	624.90
Conflict	497.88
Tonnage of food grant	
Lower Tercile	846.16
Middle Tercile	452.11
Upper Tercile	408.33
Type of food grant	
Development	614.19
Emergency	454.76
Area of recipient country	
Above median area	622.27
Below median area	454.53
Terrain ruggedness of recipie	ent country
Above median ruggedness	$375.7^{2}$
Below median ruggedness	735·91

Table 1. ITSH Cost Per Ton of Food Aid

*Note:* Internal Shipping and Handling (ITSH) figures come from the 2014-2019 IFAR reports. Before 2014, these costs were not broken out. Costs are calculated at the program level with constant 2018 dollars.

The table confirms the existence of significantly different costs to distribute food aid, even in the ITSH measure which excludes overseas shipping. There are cost efficiencies for larger programs: the cost per ton of food aid delivered decreases with the size of the program. Non-emergency (i.e. development) programs are significantly more expensive to distribute per ton than emergency (i.e. humanitarian) programs, possibly because the mean tonnage per emergency program is almost double the mean tonnage per development program in this period: 12,967 tons versus 24,059 tons. Finally, geographically large countries face higher ITSH costs.

Disbursements which on paper have similar values may represent the delivery of very different amounts of food commodities. Country size and terrain ruggedness strongly

affect ITSH. Terrain ruggedness is also associated with violent conflict (Carter, Shaver, and Wright 2019).<sup>9</sup> In other words, the error in the explanatory variable (food aid disbursements) is positively correlated with the outcome variable, which will upwardly bias estimates of the effect of humanitarian aid on conflict.

The mechanisms for how humanitarian assistance affects violent conflict center the rebel appropriation of aid. The literature on humanitarian food aid and civil conflict faces two data challenges: not all food aid is humanitarian in nature, and monetary sizes of food aid programs mask differences in how much food aid makes it to recipients. The data I present below sidestep these issues and accurately capture the theoretical quantity of interest for these mechanisms: the amount of lootable aid available for rebel appropriation.

#### 3 New data on humanitarian food aid

To resolve these data challenges, I digitized 29 years of USAID's *International Food Assistance Reports*, a yearly reporting requirement under the Food for Peace Act. In addition to narrative details on highlighted food assistance programs, these reports contain program-level data on tonnage of humanitarian food aid delivered, cost of the program, commodity type, and implementing partners. The IFARs distinguish between Title I and both types of Title II food aid.<sup>10</sup> Using tonnage is important because it alleviates

<sup>&</sup>lt;sup>9</sup>One might expect that terrain ruggedness would be positively associated with ITSH. However, rugged countries are much smaller than non-rugged countries, and two rugged countries (Ethiopia and Yemen) receive the largest programs., which creates economies of scale in aid distribution.

<sup>&</sup>lt;sup>10</sup>I use country-year measures throughout the paper, but the replication files include the raw project-level data.



Figure 1. Country-level average logged tonnage of humanitarian food aid

This figure uses IFAR data to show the average humanitarian food aid received from 1995 to 2019. The data are denominated in 1000s of metric tons. I take the log (adding 0.01) to ensure differences are legible.

potential biases in the disbursement data: a ton of food aid is identical everywhere.<sup>11</sup>

From the IFARs, I construct a longitudinal dataset of US food aid from 1991 to 2019 for every country which received any kind of food aid at least once during that period.<sup>12</sup> The datasets includes both value and tonnage for all three types of food aid. Figure I shows the average tonnage of humanitarian food aid received by the countries in the sample. The countries with the largest average receipt of humanitarian food aid are

<sup>&</sup>lt;sup>11</sup>The IFAR data cannot be disaggregated at the subnational level. Both unpacking the different modalities of humanitarian assistance and spatially disaggregating aid have costs and benefits; different data sources will be useful for different research designs.

<sup>&</sup>lt;sup>12</sup>the IFARs did not separate Title II development and humanitarian assistance before 1995, so most analyses in this paper use data from 1995 to 2019.

Ethiopia (306,423 Mts), Sudan (176,785 Mts), South Sudan (93,661 Mts), Yemen (65,082 Mts), Afghanistan (58,804 Mts), and Kenya (53,575 Mts). Ethiopia is a clear outlier: it receives both the most humanitarian food aid on average and, unlike other countries, received food aid in every year.

Figure 2 shows how the IFAR data compare to four other measurements of humanitarian aid: Nunn and Qian (2014)'s wheat aid measure, the OECD DAC measures of US humanitarian aid disbursement, Title II development food aid from USAID, and tonnage of emergency food aid from the WFP. The figure shows that these measures are strongly but not perfectly correlated and that different countries become the outliers in each data set. For example, Ethiopia and Bangladesh are the two largest recipients of wheat aid but Sudan and South Sudan are the two largest recipients of OECD disbursements. Yemen—a recent focal point for humanitarian intervention—is the fourth largest recipient of Title II humanitarian aid, but the sixth and 93rd recipient of OECD disbursements and wheat aid respectively.



Figure 2. IFAR data correlate with other measures of humanitarian aid

The Nunn and Qian data overlap with the IFAR tonnage between 1991 and 2006. The WFP data overlap with the IFAR tonnage from 1994 to 2001. All data are logged; I add 0.01 to the country averages. The Y-axis displays tonnage of humanitarian food aid from the IFAR data and the X axis displays the data listed in the headers. All data are logged.

The third panel of Figure 2 distinguishes between humanitarian and development food aid from USAID. Notable conflict zones—Afghanistan, Sudan, South Sudan, and Somalia—are well above the 45 degree line, showing that they receive significantly more humanitarian aid than development aid.

These data sidestep the problems I have mentioned previously-they capture the



Figure 3. USAID's fraction of global humanitarian aid

This figure uses data from OECD's DAC to show the fraction of global humanitarian aid provided by USAID. I omit data pre-2001 due to data discrepancies.

tonnage of humanitarian food aid delivered to a country. However, they introduce two additional sources of bias. First, USAID may target a different set of countries than the global donor community as a whole. This mismatch could bias results on the impact of humanitarian food aid. The fourth panel of figure 2 contrasts USAID's tonnage of emergency food aid with the tonnage of emergency food aid delivered by the WFP. The overall correlation coefficient between tonnage of USAID's emergency food aid and tonnage of the WFP's emergency food aid is 0.806. These figures suggest that USAIDspecific aid priorities do not significantly bias my data. Donors target food aid similarly.

Second, if USAID supplies only a small fraction of global humanitarian food aid, these estimates may still be too noisy to be useful. Using data on disbursements from the DAC, figure 3 shows the global fraction of humanitarian aid which is delivered by USAID.<sup>13</sup> USAID provides on average roughly 30 percent to 40 percent of the world's

<sup>&</sup>lt;sup>13</sup>A substantial fraction of the USAID humanitarian food assistance is distributed through multilat-

humanitarian assistance and roughly 40 percent to 70 percent of the world's emergency food assistance.<sup>14</sup>

Nevertheless, it is true that USAID's humanitarian food aid represents only a fraction of the total humanitarian food aid logged by the DAC. In addition, non-DAC donors such as China, Saudi Arabia, and private philanthropies, have increasingly contributed to humanitarian assistance in recent years. This fact introduces some unavoidable noise to estimates in this research note.<sup>15</sup> However, previous research claims a direct link between USAID humanitarian food assistance by itself and violent conflict (Nunn and Qian 2014). Even if these results cannot capture the totality of humanitarian assistance, the null findings remain informative in conversation with previous literature.

#### 4 New evidence on the humanitarian aid-conflict link

With these new data, we can re-investigate the linkage between humanitarian food aid and civil conflict. The first three papers use an instrumental variables strategy to unpack the relationship between humanitarian food aid and the incidence of conflict at a countryyear level. Nunn and Qian (2014)'s canonical paper exploits a shift-share instrumental variables design to show that US wheat aid increases conflict in recipient countries.<sup>16</sup>

eral organizations such as the World Food Programme. I exclude disbursements from multilateral donor organizations such as the WFP to avoid double-counting contributions.

<sup>&</sup>lt;sup>14</sup>In sufficiently sensitive situations, USAID also removes identifiers and logos which could tie food aid to the United States.

<sup>&</sup>lt;sup>15</sup>Non-DAC donors could also introduce interference to these results, if they coordinate with DAC donors. For example, if DAC donors avoid donating to a crisis like Yemen because non-DAC donors had already stepped in, this would also bias our results downwards. However, I found no evidence for such a process to exist.

<sup>&</sup>lt;sup>16</sup>It would be informative to replicate Nunn and Qian (2014)'s specification with their original data but confined to the overlap in samples between the original paper and this paper. However, the Food and Agriculture Organization (FAO) no longer produces the US wheat aid data on which Nunn and Qian rely

		Intrastate conflict	
	Nunn and Qian	Christian and Barrett	Mary and Mishra
Panel A: OLS Estimates			
Humanitarian food aid (1000MTs)	0.0007	0.0000	0.0010
	( 0.0003)	( 0.0002)	( 0.0008)
R^2	0.6263	0.7587	0.9234
Panel B: Reduced Form Estimates			
Instrument	0.0000	-0.000I	0.5195
	( 0.0001)	( 0.0001)	( 1.3999)
R^2	0.6240	0.7724	0.9144
Panel C: 2SLS Estimates			
Instrumented food aid (1000MTs)	0.0010	-0.0003	0.0004
	( 0.0014)	( 0.0011)	( 0.0008)
R^2	0.6187	0.7618	0.8968
Panel D: First-Stage Estimates			
Instrument	0.0844	0.0710	-18.4271
	( 0.0441)	( 0.0460)	( 58.1926)
Kleibergen-Paap F-statistic	3.6601	2.3823	0.1003
Number of observations	1863	1863	2023
Nunn and Qian Controls	X	X	0
Unit-specific cubic time trends		Х	Х
Mary and Mishra Controls			Х

#### Table 2. Humanitarian food aid does not increase conflict

*Note:* This table replicates the main findings from Nunn and Qian (2014), Christian and Barret (2017), and Mary and Mishra (2020). Estimates are from a linear probability model. The unit of observation is the country-year. The binary outcome variable is whether an intrastate war exists in a given country-year. Standard errors are clustered at the country level. Tables A.5 and A.6 list data sources and control variables.

They instrument US food assistance for country i by interacting the US wheat harvest in the previous year with the total number of years in the sample that country i received any wheat aid. Christian and Barret (2024) critique this decision by showing that much of the effect of food aid on conflict is absorbed by unit-specific time trends. Finally, Mary and Mishra (2020: 3) exploit the displacement of humanitarian aid by major crises and instrument humanitarian food aid in country i using "the share of humanitarian food aid

and the IFAR data do not allow me to back out the quantity of specific commodities. In addition, the procurement policy which linked US wheat production and USAID's commodity food aid ended in 1996, so even if the FAO data were available, the first-stage of the 2SLS specification would report either no effect or a spurious relation (Christian and Barret 2024).

out of total aid averaged across all sampled countries other than country i." I replicate these models below using identical specifications and control variables.<sup>17</sup>

Table 2 shows both the results of the instrumental variables designs and the reasons for caution. All three instruments are weak when the endogenous variable in the 2SLS estimation is food aid tonnage. Errors are heteroskedastic in all three specifications due to the structure of the panel data, so a Kleibergen-Paap F-statistic is a better test for weakness than conventional F-statistics (Andrews, Stock, and Sun 2019: 737). The Kleibergen-Paap F-statistic is well below the conventional threshold of 10 for all models. With weak instruments, the 2SLS coefficients are biased towards the OLS estimator of Panel A (Angrist and Pischke 2009: 205). Nevertheless, all three 2SLS estimates are statistically insignificant.<sup>18</sup> Using Nunn and Qian's design, our 95 percent confidence interval for the effect of food aid on the incidence of civil conflict excludes any coefficient outside of (-0.0001, 0.0001); in other words, this results supports the conclusion that humanitarian food aid does not increase civil conflict (Rainey 2014).<sup>19</sup>

The instrumental variables design is meant to counter endogeneity: humanitarian food aid may lead to conflict, but conflict certainly leads to humanitarian food aid. By finding a third variable which affects humanitarian food aid but is unrelated to civil conflict, the hope is to isolate the effect of humanitarian food aid on civil conflict. These weak 2SLS estimates are upwardly biased in the direction of the OLS estimate because

<sup>&</sup>lt;sup>17</sup>Because the IFAR reports contain only food aid data, I use data from the OECD DAC to construct this instrument.

<sup>&</sup>lt;sup>18</sup>In place of Nunn and Qian's interaction of US wheat production in year t - 1 with a county's propensity to receive food aid, I interact total US food aid to all countries with a given country's propensity to receive food aid.

<sup>&</sup>lt;sup>19</sup>I report these results in the appendix (table A<sub>5</sub>). Tables A.1 to A.4 fully replicate the main tables of each of these papers.

it fails to isolate the single direction (Angrist and Pischke 2009: 205). While the weak instrument will increase the variance of the 2SLS estimator, the coefficient on food aid in the 2SLS estimator should still be less than that of the OLS estimator, because the OLS estimator includes both the effect of humanitarian food aid on conflict and the effect of conflict on humanitarian food aid. In other words, the null result for the OLS estimator represents an upper bound to the relationship between humanitarian food aid and civil conflict using these data.

The IFAR data also allow a deeper delve into the mechanisms through which humanitarian food aid could influence violent conflict. If humanitarian food aid has a positive association with humanitarian because rebels appropriate it, then the association between the two should be stronger where the ease of appropriation is higher. The IFAR data provide two measures of the ease of expropriation: the number of implementing partners and the cost per ton of food aid (i.e tonnage divided by value). Implementing partners are the NGOs and INGOs with whom USAID partners to deliver the food aid. Implementing partners manage the 'last mile' distribution of food commodities. As food aid is spread between more implementing partners, there are more points at which food aid could be stolen. If more easily appropriated food aid increases the likelihood of conflict, we would expect a positive and statistically significant interaction between food aid and the number of implementing partner.

Similarly, cost per ton of food aid increases with the difficulty in transporting food aid within countries.<sup>20</sup> The cost per ton of food aid will increase with the elevation and terrain ruggedness of the recipient country. Both elevation and terrain cover provide

 $<sup>^{20}{\</sup>rm I}$  use cost per ton here rather than ITSH because the latter are broken out in the IFARs only beginning in 2014.

	Conflict Incidence				
	(1)	(2)	(3)	(4)	(5)
Tonnage (1000MTs)	0.177 (0.891)	0.177 (0.892)	0.177 (0.891)	0.156 (0.882)	0.311 (0.924)
Value (millions of USD)	0.001+	0.001+	0.001+	0.001+	0.001+
Tonnage * Value	(0.000)	(0.000) -0.002 (0.001)	(0.000)	(01000)	-0.002
Tonnage * N. of partners		(0.001)		0.035	(0.001)
Value * N. of partners				(0.047)	0.000
N. of partners				-0.003 (0.012)	(0.000) -0.003 (0.012)
Nunn + Qian controls	Х	Х	Х	Х	Х
Mary + Mishra controls	Х	Х	Х	Х	Х
Num.Obs.	2023	2023	2023	2023	2023
R2	0.921	0.917	0.921	0.909	0.904

Table 3. Humanitarian food aid does not increase the incidence of conflict

*Note:* The outcome variable for this table is the incidence of intrastate conflict. Explanatory variables are the tonnage of humanitarian food aid provided by USAID (in 1000MTs), the value of humanitarian food aid provided by USAID (in millions of 2018 USD), and the number of implementing partners through which the aid was delivered. Estimates are from a linear probability model where the unit of observation is the country-year. Standard errors are clustered at the country level. Data sources for control variables are listed in Tables A7 and A8; humanitarian food aid data are from the IFARs. \* p < 0.05, \*\* p < 0.01

opportunities to purloin food shipments, suggesting that appropriating food aid will be easier in countries with a higher cost per ton of food aid. I use the interaction between value and tonnage of food aid (the inverse of cost per ton); we would expect a negative interaction between tonnage and value, because high value of food aid with low tonnage of food aid implies higher cost and thus higher appropriability.

Table 3 shows no relationship between the tonnage of humanitarian food aid and the incidence of conflict. There is a positive and weakly significant (0.1 )relationship between the value of humanitarian food aid and the incidence of conflict.Moving from the 25th percentile of the value of humanitarian food aid delivered to the 75

		Risk of pe	eace failing			Risk of war	termination	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tonnage (1000MTs)			1.002	1.002			0.999	0.992 +
Tonnage * Decisive victory			(0.001)	(0.001) 0.961 (0.051)			(0.001)	(0.004)
Tonnage * Peripheral conflict				()				1.007+
Value (millions of USD)	1.000	1.000			1.000	$1.000^{*}$		(0.004)
Value * Decisive victory	(0.000)	(0.000) 1.000 (0.000)			(0.000)	(0.000)		
Value * Peripheral conflict		(0.000)				$1.000^+$ (0.000)		
Decisive victory	$0.544^{*}$	$0.561^{*}$	$0.503^{**}$	$0.537^{*}$		( )		
Peripheral conflict	(0.151)	(0.101)	(0.120)	(0.140)	1.874*** (0.317)	1.681** (0.300)	1.865*** (0.318)	1.692** (0.298)
Narang (2014) controls	Х	Х	Х	Х				
Narang (2015) controls					X	Х	Х	Х
Num.Obs.	1882	1882	2088	2088	1044	1044	1044	1044
RMSE	0.24	0.24	0.25	0.25	0.42	0.42	0.42	0.42

Table 4. Humanitarian food aid, the duration of peace, and risk of war termination

*Note:* This table re-estimates models from Narang (2014) and Narang (2015) using the IFAR data. The outcome variable in columns 1-4 is whether a peace deal fails (i.e. conflict re-emerges). The outcome variable in columns 5-8 is whether a war terminates (i.e. a peace deal is signed). Explanatory variables are the tonnage of humanitarian food aid provided by USAID (in 1000MTs), the value of humanitarian food aid provided by USAID (in millions of 2018 USD), whether the victory in the previous conflict was decisive, and whether a conflict is peripheral. Standard errors are clustered at the country level. Estimates are from a Cox Proportional Hazards model, and coefficients are displayed as odds ratios. The unit of observation is the country-year. Data sources and control variables are listed in Tables A9 and A10. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

percentile is associated with a 0.2 percentage point increase in the likelihood of conflict incidence, an increase of approximately one percent over the baseline rate of conflict incidence (0.26). There is no statistically significant interaction between either measure of the appropriability of food aid and the tonnage or value of food aid.

An alternative literature documents how violent conflict affects the duration of both war and peace. Narang (2014) argues that humanitarian food aid increases the risk of peace agreements failing, particularly where the previous conflict was ended by a decisive victory. Narang (2015) shows that humanitarian food aid increases the duration of war (i.e. decreases the risk of war termination), particularly in peripheral conflicts. Both papers test their hypotheses using a Cox proportional hazards model. Table <sub>4</sub> replicates these analyses using the IFAR data and the control variables from the original papers.

Table 4 shows no association between tonnage or value of humanitarian food aid and the risk of peace failing. However, it shows interesting results for the risk of war termination. The tonnage of humanitarian food aid slightly decreases the likelihood that a war terminates, though the effect is balanced out by a positive interaction in peripheral conflicts. The value of humanitarian food aid has a statistically significant—but substantively insignificant—positive effect on the likelihood of war termination.

This section replicated existing research designs which studied the relationship between food aid and violent conflict using the newly digitized IFAR data. The results are broadly consistent with humanitarian food aid having little or no effect on the risk of peace failing or the risk of war termination; the confidence intervals around zero exclude meaningful effects. However, there remain weakly significant results for the value of humanitarian food aid, which further illustrates the necessity of precisely measuring how much food aid is actually being delivered. By avoiding problems with other datasets including within-country transportation costs and failing to distinguish between humanitarian and non-humanitarian food aid—this research note reconciles disparate existing findings.

#### 5 Conclusion

Despite the challenges enumerated above, USAID distributed 1,315,526 metric tons of food commodities in 2019 alone. This research note introduces a new source of disaggregated, program-level data which sheds light on humanitarian food assistance. Specifically, the IFAR dataset calls into question a number of hypothesized relationships between humanitarian food aid and violent conflict (Christian and Barret 2024; Mary and Mishra 2020; Nunn and Qian 2014). Adopting the design of a variety of previous studies, I show a series of precisely estimated null results which counter arguments that humanitarian food aid makes conflict more likely, or makes conflicts last longer.

Different measurement strategies incur different costs and benefits. By showing the biases which stem from using OECD disbursements to measure humanitarian aid, this research clarifies those tradeoffs. While existing research has disaggregated humanitarian aid by geographic area, the IFAR data will help researchers to disentangle the effects of different modalities of humanitarian food aid. Specifically, the IFAR data allows researchers to distinguish between the value of humanitarian food aid and the tonnage of humanitarian food aid. This distinction, and the data which support it, grows the scope of possible empirical research about the unintended consequences of humanitarian aid.

#### 6 Acknowledgements

I thank James Fearon, David Laitin, and Jeremy Weinstein for their comments on this research note, along with everybody who discussed the manuscript at the 2021 Midwest Political Science Association annual meeting and three anonymous reviews from the Journal of Global Security Studies.

#### 7 Funding

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1656518. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation. I have no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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# Online Appendix: Feeding conflict? New data on the impact of humanitarian food aid on civil conflict

		In	trastate confl	ict	
	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: OLS Estimates					
Humanitarian food aid (1000MTs)	0.0008	0.0008	0.0007	0.0007	0.0007
	( 0.0003)	( 0.0003)	( 0.0003)	( 0.0003)	( 0.0003)
R^2	0.5925	0.5926	0.6039	0.6070	0.6263
Panel A: Reduced Form Estimates					
Instrument	0.0000	0.0000	0.0000	0.0000	0.0000
	( 0.0000)	( 0.0001)	( 0.0001)	( 0.0001)	( 0.0001)
R^2	0.5891	0.5893	0.6015	0.6048	0.6240
Panel A: 2SLS Estimates					
Instrumented food aid (1000MTs)	-0.0003	0.0000	0.0011	0.0011	0.0010
	( 0.0007)	( 0.0000)	( 0.0011)	( 0.0012)	( 0.0014)
R^2	0.5863	0.5842	0.5956	0.5981	0.6187
Panel A: First-Stage Estimates					
Instrument	0.0766	0.0736	0.0750	0.0749	0.0844
	( 0.0382)	( 0.0356)	( 0.0345)	( 0.0349)	( 0.0441)
Kleibergen-Paap F-statistic	4.0078	4.2610	4.7368	4.6014	3.6601
Number of observations	2540	2540	2288	2288	1863
Country FEs	X	X	X	X	X
Region-year FEs	X	X	Х	X	Х
US GDP per capita * avg. prob.		X	Х	X	Х
US democratic pres. * avg. prob.		Х	Х	Х	Х
Oil price * avg. prob.		Х	Х	Х	Х
Monthly recipient temp. and rainfall			X	X	X
Monthly weather * avg. prob.			Х	X	X
Avg. US military aid * avg. prob.				X	X
Avg. US economic aid * avg. prob.				Х	X
Avg. cereal imports * year FEs					X V
Avg. cereal production * year FEs					Х

#### Table A1. Humanitarian Food Aid and Conflict Incidence

*Note:* This table replicates columns 1-5 from Table 2 in Nunn and Qian (2014). Estimates are from a linear probability model. The unit of observation is the country-year. The binary outcome variable is whether an intrastate war exists in a given country-year. Standard errors are clustered at the country level. Data sources and control variables are listed in Table A.5 Column 5 is the specification used in table 2.

## A1 Full replications

In the main paper, I present abridged results which recreate findings across the literature which show humanitarian food aid affects violent conflict. In this appendix, I replicate the main tables of several of these papers.

Table A1 replicates 2 from Nunn and Qian (2014), with some modifications. Nunn

and Qian produce their parsimonious specifications using any conflict. However, the prevailing academic research most commonly links intrastate civil conflict to humnitarian aid, so I report the table using only intrastate conflicts. This means my table has two fewer columns that the original table, because Nunn and Qian report their full specifications for all conflicts, interstate conflict, and intrastate conflicts seperately.

These data also cover a different period of time than the original paper. Nunn and Qian's dataset covers 1971 to 2006. Interestingly, as Christain and Barret (2024) point out, the 1996 farm bill decoupled US food commodity purchasing from food production. My paper uses data from 1994 to 2019. One might reasonably posit that the end of the Cold War affected the relationship between humanitarian food aid and civil conflict, but both datasets contain post-Cold War conflicts.

Tables A2 and A3 replicate tables 1 and 2 in Narang (2014). This paper examines how humanitarian aid affects the probability of peace failing. The original paper operationalized humanitarian aid using data from the OECD and found that humanitarian food aid increased the risk of peace failing only when the war ended with a decisive victory. However, I show that these results are no longer significant when humanitarian aid is measured using tonnage. Once again, my data cover a different period of time: Narang (2014) covers 1989 to 2004, but my data cover 1994 to 2019.

Table  $A_4$  replicates table 1 in Narang (2015). The different columns in the original table show results from different periods of time, but I show only a specification using all years for which I have data.

Table A5 replicates Table 2 in the main paper, but replaces the tonnage of emergency food aid with the value of the emergency food aid programs reported in the IFAR reports.

Model 1 Model 2 Model 3 Model 4 Model 5 Model 6 Model 7 -0.001Humanitarian food aid 0.0020.0010.001-0.0010.000 0.000 (0.001)(0.001)(0.001)(0.001)(0.001)(0.001)(0.001) $-0.707^{**}$  $-0.637^{**}$  $-0.650^{**}$  $-0.708^{**}$ Decisive victory  $-0.686^{**}$  $-0.619^{*}$  $-0.743^{**}$ (0.254)(0.250)(0.247)(0.247)(0.241)(0.240)(0.236)Lootable resources  $0.543^{*}$  $0.558^{**}$  $0.541^{**}$ 0.2930.2760.1960.204(0.215)(0.210)(0.208)(0.201)(0.199)(0.189)(0.186) $-1.246^{***}$ Treaty -0.370 $-0.713^{*}$  $-0.729^{*}$  $-0.873^{**}$ -0.888\*\* $-0.850^{**}$ (0.357)(0.333)(0.337)(0.327)(0.329)(0.329)(0.288)Identity war -0.2280.0430.2270.2180.1220.0310.129(0.199)(0.228)(0.207)(0.206)(0.200)(0.186)(0.183)War-related deaths 0.0000.000 0.0000.0000.0000.0000.000(0.000)(0.000)(0.000)(0.000)(0.000)(0.000)(0.000)Factions -0.065-0.064-0.071-0.065-0.112-0.066-0.067(0.115)(0.114)(0.114)(0.114)(0.114)(0.114)(0.114)Democracy 0.0700.149(0.205)(0.199)Infant mortality rate  $-0.021^{***}$  $-0.016^{***}$  $-0.016^{***}$ (0.004)(0.003)(0.003)Past agreement  $-1.082^{***}$  $-0.951^{***}$  $-0.957^{***}$  $-0.692^{**}$  $-0.706^{**}$  $-0.673^{*}$ (0.303)(0.288)(0.290)(0.266)(0.268)(0.267)Government army size 0.000 +0.0000.000 $0.000^{*}$  $0.000^{*}$ (0.000)(0.000)(0.000)(0.000)(0.000)Mountainous terrain  $-0.003^{*}$  $-0.002^{*}$  $-0.002^{*}$ -0.001(0.001)(0.001)(0.001)(0.001)P-5 contiguity 0.433(0.279)Former P-5 colony 0.606\*\* (0.230)Duration of war 0.009 0.0070.0080.0110.0110.0100.005(0.009)(0.010)(0.009)(0.009)(0.010)(0.010)(0.010)

**Table A2.** Effect of Increasing Humanitarian Aid on the Risk of Peace Failing after All Civil Wars

*Note:* This table replicates table 1 in Narang (2014). Estimates are from a Cox Proportional Hazards model. Data sources are listed in Table A7. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

These data introduce a variety of noise to our quantity of interest: ITSH costs, the differential costs of different commodities, program management costs, etc.

Finally, table A6 lists all countries which appear in the IFAR data and enumerates the number of years in which they received food assistance from USAID.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Humanitarian food aid	0.002	0.001	0.001	-0.001	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Food aid * Decisive victory	-0.041	-0.044	-0.045	-0.050	-0.049	-0.047	-0.052
	(0.053)	(0.052)	(0.052)	(0.054)	(0.054)	(0.054)	(0.055)
Decisive victory	$-0.623^{*}$	$-0.544^{*}$	$-0.571^{*}$	$-0.617^{*}$	$-0.656^{**}$	$-0.625^{*}$	$-0.547^{*}$
	(0.261)	(0.257)	(0.255)	(0.256)	(0.250)	(0.249)	(0.245)
Lootable resources	$0.554^{*}$	$0.570^{**}$	$0.554^{**}$	0.308	0.291	0.206	0.216
	(0.216)	(0.210)	(0.208)	(0.201)	(0.199)	(0.189)	(0.186)
Treaty	-0.372	$-0.704^{*}$	$-0.718^{*}$	$-0.861^{**}$	$-0.876^{**}$	$-0.838^{*}$	$-1.227^{***}$
	(0.356)	(0.333)	(0.336)	(0.327)	(0.329)	(0.329)	(0.287)
Identity war	-0.217	0.046	0.057	0.242	0.231	0.137	0.129
	(0.228)	(0.207)	(0.206)	(0.201)	(0.199)	(0.186)	(0.183)
War-related deaths	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Factions	-0.108	-0.063	-0.063	-0.061	-0.061	-0.068	-0.062
	(0.115)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Democracy	0.064	0.142					
	(0.205)	(0.199)					
Infant mortality rate	$-0.021^{***}$	$-0.016^{***}$	$-0.016^{***}$				
	(0.004)	(0.003)	(0.003)				
Past agreement	$-1.060^{***}$	$-0.934^{**}$	$-0.940^{**}$	$-0.681^{*}$	$-0.696^{**}$	$-0.662^{*}$	
	(0.303)	(0.288)	(0.290)	(0.266)	(0.267)	(0.267)	
Government army size	0.000*	$0.000^{*}$	0.000+	0.000	0.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Mountainous terrain	$-0.003^{*}$	$-0.002^{*}$	$-0.002^{*}$	-0.001			
	(0.001)	(0.001)	(0.001)	(0.001)			
P-5 contiguity	0.410						
	(0.279)						
Former P-5 colony	$0.607^{**}$						
	(0.231)						
Duration of war	0.008	0.007	0.007	0.010	0.010	0.009	0.005
	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)

Table A3. Effect of Humanitarian Aid on the Risk of Peace Failing after Decisive/Nondecisive Victories

*Note:* This table replicates table 2 in Narang (2014) Estimates are from a Cox Proportional Hazards model. Data sources are listed in Table A7. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

	Model 1	Model 2
Humanitarian food aid	-0.001	$-0.009^{*}$
	(0.001)	(0.004)
Peripheral conflict		$0.536^{**}$
		(0.176)
Food aid * Peripheral		$0.009^{*}$
		(0.004)
Deaths (lagged)	$0.000^{*}$	0.000 +
	(0.000)	(0.000)
Population (logged)	$-0.230^{***}$	$-0.300^{***}$
	(0.067)	(0.070)
GDP per capita	0.000	0.000
	(0.000)	(0.000)
Polity2 Score	0.012	0.010
	(0.016)	(0.015)
Diamonds	0.058	0.047
	(0.167)	(0.168)
Drugs	0.146	0.077
	(0.195)	(0.198)
Guarantee	-0.544	-0.338
	(1.175)	(1.241)
Rugged terrain	0.001	0.000
	(0.001)	(0.001)
Forest cover	-0.002	-0.001
	(0.002)	(0.002)

Table  $A_4$ . Humanitarian food aid and the risk of civil war termination

*Note:* This table replicates column 2 of Tables I and 2 from Narang (2015). Estimates are from a Cox Proportional Hazards model. Data sources are listed in Table A8. \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

	Intrastate conflict			
	Nunn and Qian	Christian and Barrett	Mary and Mishra	
Panel A: OLS Estimates				
Humanitarian food aid (mil. of USD)	0.0008	0.0000	0.0004	
	( 0.0003)	( 0.0002)	( 0.0003)	
R^2	0.6277	0.7587	0.9169	
Panel B: Reduced Form Estimates				
Instrument	-0.000I	-0.000I	0.5195	
	( 0.0001)	( 0.0001)	( 1.3999)	
R^2	0.5997	0.7545	0.9144	
Panel C: 2SLS Estimates				
Instrumented food aid (mil. of USD)	0.0010	-0.0003	0.0026	
	( 0.0014)	( 0.0011)	( 0.1957)	
R^2	0.6225	0.7639	-22.1274	
Panel D: First-Stage Estimates				
Instrument	0.0850	0.0601	-1.1251	
	( 0.0438)	( 0.0360)	( 98.1712)	
Kleibergen-Paap F-statistic	3.7745	2.7951	0.0001	
Number of observations	1863	1863	2023	
Nunn and Qian Controls	X	X	ů.	
Unit-specific cubic time trends		Х	Х	
Mary and Mishra Controls			X	

#### Table A5. Value of Humanitarian Food Aid and Conflict Incidence

*Note:* This table replicates table 2 in the main paper, but uses the value of humanitarian food aid (derived from the IFAR reports) rather than tonnage. Data are in millions of constant 2018 dollars. Estimates are from a linear probability model. The unit of observation is the country-year. The binary outcome variable is whether an intrastate war exists in a given country-year. Standard errors are clustered at the country level. Data sources are listed in Tables A.5 and A.6

	Years receiving aid				
Country	Emergency	Development	Combined	Any	
Afghanistan	23	3	2	25	
Albania	3	0	2	5	
Algeria	IO	0	0	IO	
Angola	13	5	4	17	
Armenia	7	0	I	8	
Azerbaijan	8	0	0	8	
Bangladesh	9	<sup>2</sup> 5	3	28	
Benin	0	12	4	16	
Bhutan	0	0	2	2	
Bolivia	0	I4	4	18	
Bosnia & Herzegovina	4	0	I	5	
Botswana	0	I	3	4	
Brazil	0	0	3	3	
Bulgaria	2	0	0	2	
Burkina Faso	9	23	3	28	
Burundi	23	13	3	26	
Cambodia	3	4	I	6	
Cameroon	13	5	I	18	
Cape Verde	0	12	4	16	
Central African Republic	16	5	4	25	
Chad	18	19	3	28	
Colombia	16	0	I	17	
Comoros	0	I	2	, 3	
Congo - Brazzaville	12	0	3	15	
Congo - Kinshasa	17	II	0	17	
Costa Rica	0	2	3	، 5	
Croatia	0	0	I	I	
C´te d'Ivoire	II	4	3	18	
Diibouti	21	2	I	23	
Dominican Republic	I	6	4	10	
Ecuador	4	4	т 2	IO	
Egypt		4	2	II	
El Salvador	8	3	- 2	13	
Equatorial Guinea	0	J	0	J	
Eritrea	8	8	I	12	
Eswatini	2	0	2		
Ethiopia	25	24	-	20	
Gambia	-3	-4	4	-9 17	
Georgia	3 8	0	4 T	-7	
Ghana	0	15	1	9 10	
Guatemala	U U	1.0 2.2	4	26	

Table A6. Countries represented in the IFAR data

Guinea	ю	15	2	18
Guinea-Bissau	2	3	4	9
Guyana	0	3	2	5
Haiti	16	<sup>2</sup> 3	4	28
Honduras	8	15	4	20
India	I	16	3	19
Indonesia	7	9	3	14
Iran	0	0	I	I
Iraq	6	0	2	7
Jamaica	0	I	2	3
Jordan	0	2	I	3
Kenya	$^{25}$	18	4	29
Laos	2	2	I	5
Lebanon	2	0	3	5
Lesotho	3	5	4	II
Liberia	18	13	4	25
Libya	I	0	0	I
Madagascar	II	24	4	28
Malawi	8	18	4	25
Mali	15	IO	4	25
Mauritania	15	18	4	28
Mauritius	0	I	3	4
Mexico	0	I	5 4	5
Mongolia	0	0	I	I
Morocco	0	2	4	6
Mozambique	9	15	4	25
Myanmar (Burma)	4	0	0	4
Namibia	I	0	0	I
Nepal	IД	3	2	17
Nicaragua	9	Ід	4	18
Niger	16			28
Nigeria	5			5
North Korea	9	0	0	9
North Macedonia	I	0	I	2
Pakistan	21	7	3	24
Palestinian Territories	16	· 0	3 4	20
Panama	0	Ι	4	5
Paraguay	0	I	2	3
Peru	0	12	4	16
Philippines	5	2		IO
Russia	3	0	0	3
Rwanda	18	12	2	21
Senegal	5	12	3	10
Serbia	2	0	0	2
Sierra Leone	12	Ι <i>Δ</i>	4	24
Slovenia	-5	-4	-4 I	-+ T

25	0	4	29
9	3	0	9
9	5	Ι	13
25	I	4	29
5	0	0	5
0	2	4	6
13	3	0	14
23	4	0	22
0	0	Ι	Ι
5	0	0	5
0	I	4	5
0	I	0	Ι
25	21	4	29
12	6	2	20
8	II	Ι	14
14	6	I	15
	25 9 25 5 0 13 23 0 5 0 5 0 25 12 8 14	$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\begin{array}{cccccccccccccccccccccccccccccccccccc$

#### A2 Data sources for control variables

Across the paper, I reproduce specifications from five different papers that estimate the effect of food aid on humanitarian outcomes. In tables A7-A10, I enumerate the sources for the control variables used by each of these papers. Christian and Barret (2024) use the same control variables as Nunn and Qian (2014)—albeit with the addition of country-specific cubic time trends—so I do not include a separate table for the paper.

Variable	Operationalization	Source
US real per capita GDP	US GDP per capita in constant 2020 dollars	World Bank
US democratic president	Binary measure for whether the US president is a democrat	Hand coded
Oil price	Cushing, OK crude oil (dollars per barrel)	US Energy Information Administration
Monthly recipient temperature	Mean monthly temperature	Willmott, C. J. and K. Matsuura, Terrestrial Air Temperature: 1900-2017 Gridded Monthly Time Series(1900 - 2017)
Monthly recipient precipitation	Mean monthly precipitation	Willmott, C. J. and K. Matsuura, Terrestrial Air Temperature: 1900-2017 Gridded Monthly Time Series(1900 - 2017)
Average US military aid	US military aid per capita	US government (Foreignassistance.gov)
Average US economic aid	US economic aid per capita (excluding humanitarian aid)	US government (Foreignassistance.gov)
Average recipient cereal imports	1000 MTs of cereals	FAOSTAT detailed trade matrix
Average recipient cereal production	1000 MTs of cereals	FAOSTAT

Table A7. Control variables from Nunn and Qian (2014)

Variable	Operationalization	Source
Non-food aid per capita, logged	US military aid per capita	US government(Foreign assistance.gov)
Non-humanitarian food aid per capita	US Title 2 development food aid (1000MTs)	IFAR reports
Ethnic tensions	Percent of population excluded from power	Ethnic Power Relations dataset
Polity 2 score	Polity 2 score	Polity data
GDP per capita, log	GDP per capita in constant 2020 dollars	World Bank
Inflation, log	Annual change in a consumer price index	World Bank
Humanitarian food aid in neighbor countries	Humanitarian food aid (1000 MTs) in neighboring countries, weighted by shared border length	IFAR reports
Conflict in neighbor countries	Weighted average of a binary measure of conflict incidence	Uppsala Conflict Data Program
Weather controls	Monthly mean temperature, monthly mean precipitation	Willmott, C. J. and K. Matsuura, Terrestrial Air Temperature: 1900-2017 Gridded Monthly Time Series(1900 - 2017)

## Table A8. Control variables from Mary and Mishra (2020)

Variable	Operationalization	Source
Decisive victory	Complete victory for side A or side B	Kreutz, Joakim. 2010. How and When Armed Conflicts End: Introducing the UCDP Conflict Termination Dataset. Journal of Peace Research 47(2).
Lootable resources	diamonds or coca	Lujala, Päivi 2010. The Spoils of Nature: Armed Civil Conflict and Rebel Access to Natural Resources. Journal of Peace Research 47(1): 15–28
Identity War	Incompatibility over territory	Kreutz, Joakim. 2010. How and When Armed Conflicts End: Introducing the UCDP Conflict Termination Dataset. Journal of Peace Research 47(2).
Conflict deaths	Sum of deaths in a conflict episode	Pettersson, Therese, Shawn Davis, Amber Deniz, Garoun Engström, Nanar Hawach, Stina Högbladh, Margareta Sollenberg & Magnus Öberg (2021). Organized violence 1989-2020, with a special emphasis on Syria. Journal of Peace Research 58(4).
Infant Mortality	Deaths per 1000 births	World Bank. Mortality rate, infant (per 1,000 live births)
Military Size	Armed forces personnel, total (1000s)	International Institute for Strategic Studies, The Military Balance.
Terrain ruggedness	Average terrain ruggedness	Andrew Shaver, David B. Carter, Tsering Wangyal Shawa. 2019. Terrain Ruggedness and Land Cover: Improved Data for All Research Designs" in Conflict Management and Peace Science 36(2).
P5 colony	Binary indicator	Hand coded
P5 contiguous	Binary indicator	Hand coded

## Table A9. Control variables from Narang (2014)

Variable	Operationalization	Source
Conflict deaths	Sum of deaths in a conflict episode	UCDP Battle-Related Deaths Dataset version 21.1
Population	Log of total population	World Bank
Polity 2 score	Polity 2 score	Polity data
GDP per capita, log	GDP per capita in constant 2020 dollars	World Bank
Diamonds	Binary indicator	Lujala, Päivi 2010. The Spoils of Nature: Armed Civil Conflict and Rebel Access to Natural Resources. Journal of Peace Research 47(1): 15–28
Drugs	Binary indicator	Lujala, Päivi 2010. The Spoils of Nature: Armed Civil Conflict and Rebel Access to Natural Resources. Journal of Peace Research 47(1): 15–28
Guarantee	UCDP peace agreement indicator	Pettersson, Therese; Stina Högbladh & Magnus Öberg (2019) Organized violence, 1989-2018 and peace agreements. Journal of Peace Research 56(4)
Mountains	Mean elevation (aggregated from a 1km by 1km raster)	Andrew Shaver, David B. Carter, Tsering Wangyal Shawa. 2019. Terrain Ruggedness and Land Cover: Improved Data for All Research Designs" in Conflict Management and Peace Science 36(2).
Forests	Mean forest cover (aggregated from a 1km by 1km raster)	Andrew Shaver, David B. Carter, Tsering Wangyal Shawa. 2019. Terrain Ruggedness and Land Cover: Improved Data for All Research Designs" in Conflict Management and Peace Science 36(2).

## Table A10. Control variables from Narang (2015)