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

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Abstract

Does humanitarian food aid increase violent conflict? Anecdotal and empirical evidence suggests a link. However, previous measures of humanitarian food aid suffer from two problems: (1) they fail to account for differences in within-country transportation costs and (2) they conflate humanitarian and non-humanitarian food aid. I introduce a new dataset of USAID humanitarian food assistance across 103 countries from 1991 to 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 no relation between humanitarian food aid and the incidence of conflict, conflict termination, or the duration of peace. These results do not change when I use these new data to proxy for the ease of appropriating humanitarian aid. By introducing new program-level data, this paper provides evidence on a disputed linkage and advances the literature on the unintended consequences of humanitarian assistance.

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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). In the Sudan, aid groups paid checkpoint fees to Janjaweed militias to cross rebel-controlled areas (Jaspers 2018, p. 141). Academic research has generalized these anecdotes. Scholars have argued that humanitarian aid prolongs war (Narang 2015; Nunn and Qian 2014), increases the intensity of conflict (Wood and Molfino 2016); or makes conflicts less likely (Mary and Mishra 2020).

This paper shows that when humanitarian food aid is measured with a closer accord to proposed mechanisms, there is essentially no evidence that food aid prolongs, intensifies, or reduces conflict. While some recent articles have raised methodological concerns about the food aid-civil conflict relationship (Christian and Barret 2021), I show that the lack of a relationship is robust to a more theoretically targeted measure which addresses the methodological concerns. Re-estimating a number of previous research designs using these data, I find no relationship between humanitarian food aid and conflict incidence. I find no relationship between humanitarian food aid and the risk of peace failing and only a weak relationship with war termination. These data allow me to investigate differences in how easy food aid is to appropriate across contexts, but I show that neither the number of implementing partners nor the cost per ton of food aid affects the level of violent conflict.

A lack of disaggregated data forced previous studies of this phenomenon to rely on measures which for two reasons only weakly proxy for humanitarian food 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. Including such costs means that identically valued disbursements may correspond to substantially different amounts of humanitarian assistance. Second, not all food aid is humanitarian aid. A significant portion of the US Agency for International Development (USAID)'s food aid portfolio comprises longer-term development projects.

This paper introduces project-level data on food assistance programs from USAID—the largest provider of humanitarian food aid in the world.[1] I digitized 29 years of USAID's *International Food Assistance Reports* (IFARs) which are congressionally mandated summaries of all USAID food assistance programming. These granular data span all recipients of US food assistance from 1991 to 2017, and they avoid both of the biases which trouble previous measures of humanitarian food aid.[2] First, these data include the intended use of food aid, which allows me to subset only to true humanitarian food assistance. Second, these data measure the tonnage of food aid shipped rather than value of food assistance programs. The former excludes the within-country shipping costs; ten tons of food aid in one country is the same as ten tons of food aid in another. By increasing the granularity and precision with which humanitarian aid can be measured, the IFAR dataset will broaden the scope of empirical questions about unintended consequences of humanitarian food aid which researchers can answer.

The paper proceeds in five parts. The first section unpacks the theory behind the humanitarian food aid-civil conflict nexus to identify the precise quantity of theoreti-

[1] In 2019, USAID alone provided 51.6 percent of global emergency food aid disbursements according to the OECD.

[2] By bias, I refer to the presence of systematic errors between the data and the quantity of interest—in this case, the amount of food aid expropriable by armed groups.

cal interest. The second section examines the problems with preexisting measures of humanitarian assistance. The third section introduces the new IFAR data. The fourth section examines the relationship between humanitarian food aid and violent conflict in light of these new data. The fifth section concludes the paper.

1 Humanitarian food aid and conflict

Anecdotal evidence and an academic literature both support the humanitarian aid-civil conflict nexus. Unlike development aid, humanitarian aid is an immediately fungible conflict resource. It has the potential for both direct effects on rebel capacity and indirect effects on the bargaining range between rebels and the state. These factors create an expectation that humanitarian food aid would be positively associated with violent conflict.

Anecdotes about stolen humanitarian aid supporting rebels are common. Humanitarian assistance to refugee camps in the Eastern Congo, for example, supplied Hutu raids into neighboring Rwanda (Gourevitch 1999). More recently, Houthi rebels in Yemen have stolen food aid and "diverted it to front-line combat units or sold it for profit on the black market" (Michael 2020). By providing these lootable resources which are necessary to continue fighting, humanitarian assistance can help armed groups continue their fighting, thus prolonging armed conflict.[3]

An extensive literature reinforces these anecdotes by arguing that humanitarian food

[3] Another branch of the literature studies project-level effects of 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 (Crost et al. 2014; De Juan 2019; Child 2019). For a similar logic applied to humanitarian aid, see: Wood and Sullivan (2015).

aid drives conflict (Nunn and Qian 2014). Humanitarian food aid is distinct as a conflict resource because it is immediately fungible. Humanitarian aid projects provide food and other immediately useful goods: blankets, mosquito nets, tarps, nutritional supplements, etc. Such goods are essential for armed groups to continue the fight (Fearon and Laitin 2003; Koren and Bagozzi 2017). Poorly fed, nutrient-deficient, or otherwise ill-supplied rebels will be less effective. If the armed groups' recruits are not well motivated, providing such goods may also be necessary to maintain discipline (Weinstein 2007). Moreover, humanitarian aid can also be easily monetized to purchase arms or ammunition. There is always a market for food; stolen irrigation pumps provided by development projects may be harder to offload.

In contrast, development aid might also increase the duration of civil conflict by promoting rent-seeking behavior by armed groups (Findley et al. 2011). However, it is unclear the extent to which development aid is immediately fungible. 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 means there is no money to be appropriated in the implementation area, and the goods, such as excavation equipment or pipes, have only limited value or applicability to conflict. Agricultural extension programs have similar constraints: the money changes hands far from the implementing area. It is hard to imagine how building an irrigation perimeter produces more than a small number of goods which can be taken to support an armed group. These programs may still produce conflict in the long term—an irrigation perimeter is a valuable asset that could be contested—but short term appropriation by violent actors is harder to conceive.

Beyond direct effects on how long armed groups can fight, humanitarian assistance may have an indirect effect on the bargaining range between armed groups and the states they fight. Humanitarian assistance tends to be targeted towards the losing side of conflict (Narang 2014). This dynamic induces a commitment problem: if the weaker side has been strengthened by humanitarian aid, it has a greater incentive to renege on agreements it negotiated before the provision of humanitarian aid. Moreover, providing foreign aid can increase uncertainty in bargaining between the state and the armed group (Narang 2014). This uncertainty complicates the peace-making process and prolongs the conflict. These mechanisms seem 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 the balancing effect of humanitarian aid.

These direct and indirect effects suggest that humanitarian and non-humanitarian food aid will have different effects on violent conflict, and so it is necessary to distinguish between them. Putting these items together, the precise quantity of interest which underlies the theories would be the exact amount of purely humanitarian aid delivered.

2 Measuring humanitarian food aid

The OECD's Development Assistance Committee (DAC) keeps the most commonly used records of foreign aid commitments and disbursements by donor states. These data are comprehensive; their standardization of reporting across donors allows cross-country analysis of aid flows with relative ease. Most studies of humanitarian food aid and violent conflict use these data (Narang 2015; Narang 2014; Mary and Mishra 2020; Zürcher 2017). These data are also one of the inputs to AidData, another source data of on humanitarian assistance (Wood and Molfino 2016; Goodman et al. 2019). However, the data fail to account for within-country differences in transportation costs between humanitarian aid disbursements.

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 11 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." [4] USAID categorizes the costs as Internal Shipping and Handling (ITSH). The transportation costs reveal that the disbursements recorded by the DAC may not be accurate measures of the true amount of humanitarian aid delivered to recipients.

ITSH costs are not uniform by country. The geography of some countries presents challenges to food distribution. In the Democratic Republic of the Congo, long distances and poor infrastructure increases transportation costs. By contrast, humanitar-

[4] These statistics come from pages 15-16 of the 2019 IFAR report; the report characterizes the remaining funds as 'other.'

Table 1. ITSH Cost Per Ton of Food Aid

	Mean Dollars per Ton
Presence of conflict	
Peace	624.90
Conflict	493.83
Tonnage of food grant	
Lower Tercile	844.71
Middle Tercile	447.89
Upper Tercile	406.98
Type of food grant	
Development	610.46
Emergency	454.76
Area of recipient country	
Above median area	622.27
Below median area	450.02

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.

ian 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. Political obstacles, of course, remain possible. More broadly, large distances or rugged terrain increase the cost of ITSH. Consequently, disbursements which on paper have similar values may represent the delivery of quite different amounts of food commodities.

Table 1 shows the average ITSH cost per ton for different subgroups of Title II programs. The table confirms the existence of significantly different costs to distribute food aid, even within the ITSH category which excludes overseas or inland 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 average tonnage per emergency program is almost double the average size per development program in this period: 12,967 tons versus 24,059 tons. It is also worth noting that these averages are driven by extremely large programs in Yemen and Ethiopia, which together constitute 52 percent of all food aid shipped in this period. Finally, geographically large countries higher ITSH costs.

Differences between food aid categories are the second problem with using OECD disbursement data. Within US food assistance programs, using raw 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.[5] The multiple modalities within this legislation create significant heterogeneity within US food aid. 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. In 2017, for example, USAID used

[5] 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.

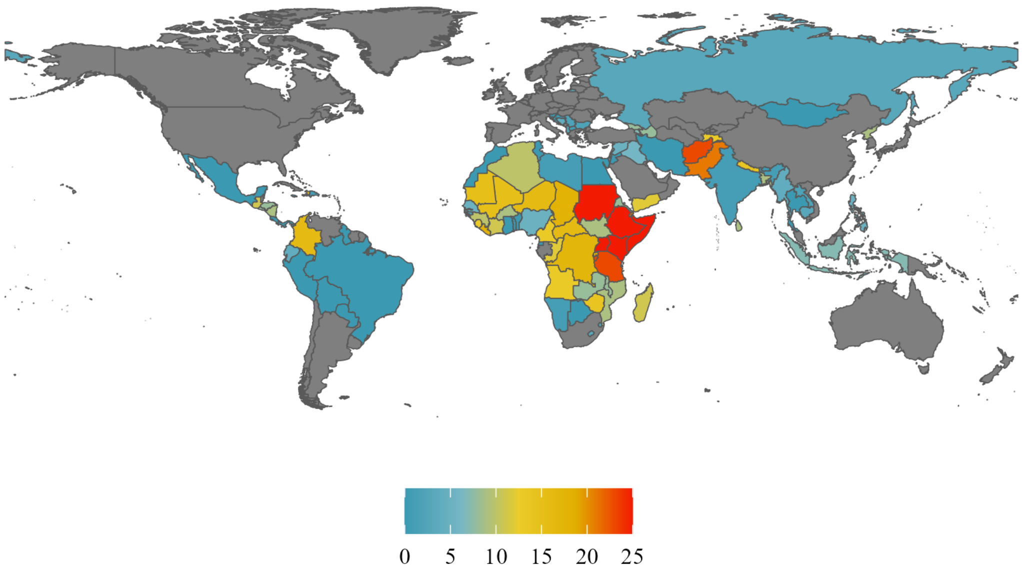
Title II development programs to encourage crop diversification and conservation of soil and water in Burkina Faso. Finally, Title II emergency assistance provides food commodities to implementing partners, which then distribute in-kind food assistance to local beneficiaries. Only Title II emergency 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 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: monetary sizes of food aid programs mask differences in how much food aid makes it to recipients, and not all food aid is humanitarian in nature. The data I present below accurately capture this theoretical quantity of interest: the amount of fungible aid available for rebel appropriation. They avoid the costs associated with shipping food aid to distribution points and they isolate the aid which rebels can easily appropriate.

3 New data on humanitarian food aid

To resolve these data challenges, I digitized 29 years of USAID's ***International Food Assistance Reports***. These reports are a yearly requirement under the Food for Peace Act, which means they are published regardless of political considerations. 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,

Figure 1. Number of years since 1995 that a country received humanitarian food aid



This figure uses IFAR data to count the number of years from 1995 to 2019 (inclusive) in which a country received emergency food aid from USAID. Countries in grey do not appear in the IFAR data.

commodity type, and implementing partners. The IFARs distinguish between Title I and both types of Title II food aid.[6]

From this database, I construct a longitudinal dataset of US food aid from 1991 to 2019 for every country which received food aid at least once.[7] I include every country which received some form of food aid from USAID between 1991 and 2019.Figure 1 shows the number of years in which a country receives humanitarian food aid in my sample. The full list of countries represented in the data appears in table A.6. In total,

[6]I use country-year measures throughout the paper, but the replication files include the raw project-level data. The codebook includes more detail on the IFAR reports.

[7]However, most analyses in this paper use data from 1995 to 2019 because the IFARs did not separate Title II development and humanitarian assistance before then.

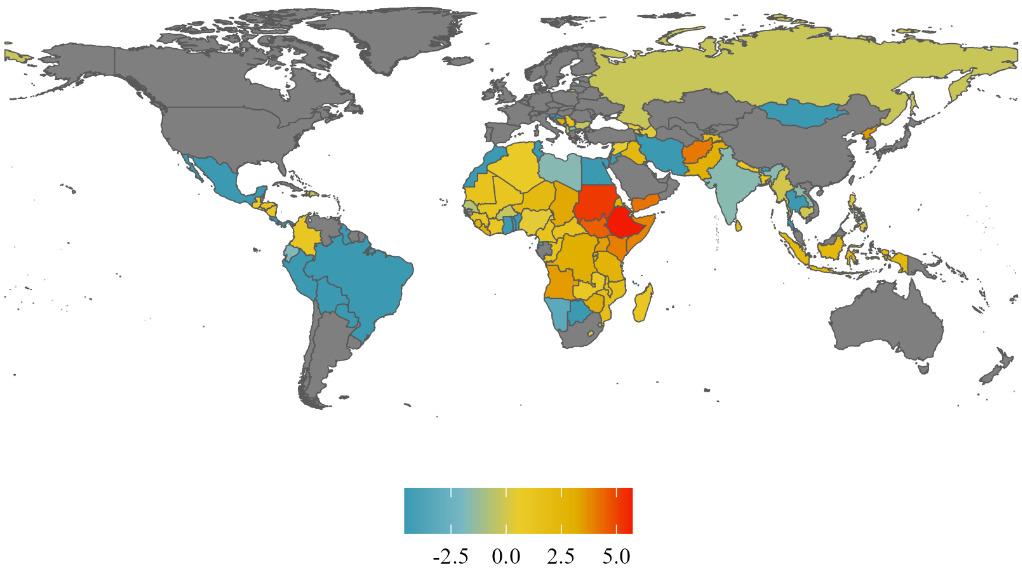
103 countries are included. However, 28 of these countries did not receive humanitarian food aid in any year of the sample. Of these 28, 19 received both development food assistance and food assiatance delivered between 1991 and 1994. Seven received food aid between 1991 and 1994 and no subsequent development food assistance. Two (Equatorial Guinea and Tunisia) received only post-1994 development food assistance. The most frequent recipients of humanitarian food aid in this period were Uganda and Ethiopia (25 years each—every year in the sample) followed by Afghanistan, Tanzania, Burundi (23 years each), Djibouti, and Pakistan (23 years each).[8]

Figure 2 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 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 received food aid in every year. Looking at the country-year observations, seven of the top ten yearly tonnages of humanitarian food aid went to Ethiopia. Another top-ten observation was Yemen (in 2019) and the remaining two observations were for the Sudan (2004 and 2006).

Beyond descriptive statistics, it is important to situate the IFAR data within the broader literature on humanitarian aid. Figure 3 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

[8] One surprise on the maps is Russia, which received humanitarian food aid programmed through the WFP (mostly wheat flour) from 2003 to 2005.

Figure 2. Logged average tonnage of humanitarian food aid across years



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. Countries in grey do not appear in the IFAR data.

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 3. Country averages of different measures of humanitarian food aid

Note: 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 the IFAR tonnage data and the X axis displays the data I list in the headers.

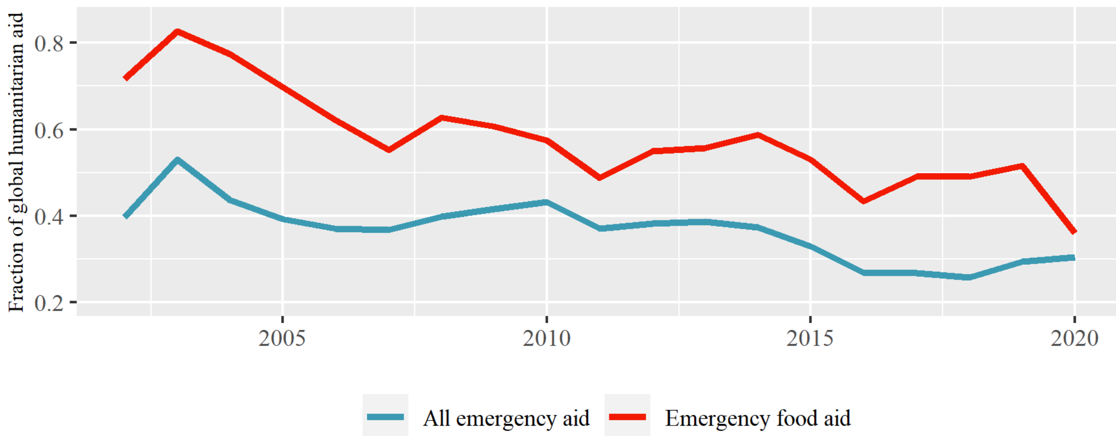
The third panel of Figure 3 distinguishes between humanitarian and development food aid from USAID. Notable conflict zones—Afghanistan, Sudan, South Sudan, and Somalia—are well above the 45 degree line, showing that they receive significantly more humanitarian aid than development aid. Ethiopia receives a large amount of both types of aid. Bangladesh, India, and Ghana receive a tremendous amount of development aid but relatively little humanitarian aid. Most countries, however, receive small to zero amounts of both development and humanitarian food aid.

These data sidestep the problems I have mentioned previously. However, the data do introduce two potential sources of bias. First, foreign policy pressures may lead USAID to target a different set of countries than the global donor community as a whole. This mismatch would bias any results on the impact of humanitarian food aid. One way to identify the extent of this bias is to see if USAID's food assistance tracks with that of major multilateral donors. The fourth panel of Figure 3 displays the tonnage of emergency food aid delivered by the WFP—the main food assistance programmer within the United Nations system.

USAID's emergency food aid is more tightly associated with WFP food aid than with other measures of humanitarian aid. The overall correlation coefficient between tonnage of USAID's emergency food aid and tonnage of the WFP's emergency food aid is 0.806, suggesting that food aid is targeted similarly across donors. Iran, Thailand, Croatia, Jordan, and Ghana all received emergency food aid from the WFP but not from USAID (during the years of the overlap), though both Ghana and Jordan received development food aid from USAID. There are no countries which receive emergency food aid from USAID but not from the WFP. A number of countries receive emergency food aid from neither.

These figures suggest that USAID's targeting of emergency food aid tracks with that of other donors. The second potential source of bias could arise if USAID does not supply a large enough component of humanitarian food aid. 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 4 shows the distribution

Figure 4. USAID's fraction of global humanitarian aid



Note: This figure used data from OECD's DAC. The pre-2001 DAC data on USAID's humanitarian contributions are unreliable because they contrast with the figures reported in the relevant IFAR reports. I exclude these years.

over time of the global fraction of humanitarian aid which is delivered by USAID.[9] This figure shows that USAID provides on average roughly 30 percent to 40 percent of the world's humanitarian assistance. However, this figure is dramatically higher for emergency food aid specifically: roughly 40 percent to 70 percent.

Figure 4 uses OECD disbursements to calculate USAID's share of humanitarian aid because these data facilitate cross-country comparisons. However, translating from disbursements into tonnage likely undercounts USAID's share of global emergency food aid. Table 1 shows that the shipping cost per ton of emergency food aid decreases as the shipment increases in size, which likely reflects economies of scale. With USAID being the largest donor of emergency food aid, its average cost per ton to deliver the aid

[9]These data exclude disbursements from multilateral donor organizations such as the WFP to avoid double-counting contributions. The WFP's food programming largely comes from grants from donor organizations like USAID, so including the multilateral institutions creates a noisier estimate. Including emergency food aid disbursed by multilateral institutions gives qualitatively similar results.

is likely lower. As a result, Figure 2 shows a lower bound on USAID's fraction of global humanitarian food aid tonnage.

A final limitation of these data is that they exist only at the country-year level. Some of the existing literature on the relationship between food, rebel supplies, and violent conflict analyzes data at the subnational or grid cell level. Koren and Bagozzi (2017), for example, use spatially disaggregated data on cropland to show that rebel appropriation of food increases the frequency of violence against civilians during conflict. Similarly, Wood and Sullivan (2015) show that the availability of humanitarian food aid incentivizes looting—leading to greater violence against civilians by rebels, but not by state actors. AidData, a prominent source of data on international development assistance more generally, also reports subnational data. Unfortunately, the manner in which the IFARs enumerate food aid tonnage prevents these data from being available at the subnational level.

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. I first estimate a specification from Nunn and Qian (2014)'s canonical paper which exploits a shift-share instrumental variables design to show that US wheat aid increases conflict in recipient countries. They instrument US food assistance by interacting the US wheat harvest in the previous year with a country's propensity to receive food aid, i.e. the total number of years in the sample the country received any wheat aid. This paper was later critiqued by Christian and Barret (2021) who show that

Table 2. Humanitarian Food Aid and Conflict Incidence

	Intrastate conflict		
	Nunn and Qian	Christian and Barrett	Mary and Mishra
Panel A: OLS Estimates			
Humanitarian food aid (1000MTs)	0.0007	0.0000	0.0006
	(0.0003)	(0.0002)	(0.0009)
R^2	0.6215	0.7531	0.9175
Panel B: Reduced Form Estimates			
Instrument	0.0000	-0.0001	0.5128
	(0.0001)	(0.0001)	(1.3945)
R^2	0.6193	0.7669	0.9150
Panel C: 2SLS Estimates			
Instrumented food aid (1000MTs)	0.0008	-0.0003	0.0004
	(0.0013)	(0.0010)	(0.0008)
R^2	0.6137	0.7568	0.9019
Panel D: First-Stage Estimates			
Instrument	0.0835	0.0706	-17.8644
	(0.0437)	(0.0455)	(57.0883)
Kleibergen-Paap F-statistic	3.6523	2.4080	0.0979
Number of observations	1909	1909	2046
Nunn and Qian Controls	X	X	
Unit-specific cubic time trends		X	X
Mary and Mishra Controls			X

Note: This table replicates the main findings from Nunn and Qian (2014), Christian and Barret (2021), and Mary and Mishra (2020). Estimates are from a linear probability model. The outcome variable is the probability of a civil war occuring in any given year. Standard errors are clustered at the country level. Data sources are listed in Tables A.5 and A.6

much of the effect of food aid on conflict is absorbed by including unit-specific time trends. Finally, Mary and Mishra (2020, p.3) argue that humanitarian food aid actually reduces civil conflict. They exploit the displacement of humanitarian aid and instrument humanitarian food aid in country i using "the share of humanitarian food aid out of total aid averaged across all sampled countries other than country i."

Table 2 shows the results of these specifications when applied to tonnage of US humanitarian food aid. All three specifications use an instrumental variables design to overcome endogeneity, but all three instruments are weak when the endogenous variable in the 2SLS estimation is food aid tonnage rather than the original measures. With such

Table 3. Humanitarian food aid, the duration of peace, and risk of war termination

	Risk of peace failing		Risk of war termination	
	Model 1	Model 2	Model 3	Model 4
Humanitarian food aid (1000MTs)	0.002	0.002	−0.001	−0.009*
	(0.001)	(0.001)	(0.001)	(0.004)
Humanitarian food aid * Decisive victory		−0.040		
		(0.053)		
Humanitarian food aid * Peripheral conflict				0.009*
				(0.004)
Narang (2014) controls	X	X		
Narang (2015) controls			X	X
R2	0.037	0.037	0.024	0.043
n	2088	2088	1062	1062

Note: Models 1 and 2 re-estimate specifications from Narang (2014). Models 3 and 4 re-estimate specifications from Narang (2015). Estimates are from a Cox Proportional Hazards model. Data sources are listed in Tables A7 and A8. * p < 0.05, ** p < 0.01, *** p < 0.001

weak instruments, the bias of the 2SLS estimator ought to be in the direction of the OLS estimator of Panel A (Angrist and Pischke 2009). Nevertheless, all three 2SLS estimates are statistically insignificant.[10] In the appendix table A.5 I replicate this table using the value of humanitarian food aid projects derived from the IFAR reports.

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. This analysis could inform whether the difference in results is due to the change in data or the change in observed countries. However, this analysis is impossible for two reasons. First, the Food and Agriculture Organization (FAO) no longer produces the data on US wheat aid on which Nunn and Qian rely.[11] Second, Christian and Barrett (2021) point out that the connection between US wheat production and USAID's

[10] 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.

[11] The IFAR data do not allow me to back out the quantity of aid provided which came from a specific commodity such as wheat, unless wheat was the only commodity in the grant.

commodity food aid was severed in 1996. This change in procurement policies means that even if the FAO data were available, the first-stage of the 2SLS specification would report either no effect or a spurious relation.

An alternative set of literature examines 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, whereas Narang (2015) shows that humanitarian food aid increases the duration of war (i.e. decreases the risk of war termination). Both papers test their hypotheses using a Cox proportional hazards model. Table 3 recreates these analyses using the IFAR data. The only finding which remains statistically significant using the new data is the finding that humanitarian food aid decreases civil war termination—it is associated with longer wars.

The direct and indirect mechanisms through which humanitarian food aid is hypothesized to increase violent conflict both involve humanitarian aid being appropriated by armed groups. These mechanisms suggest that the effect of humanitarian food aid on violent conflict would be greater when the humanitarian aid is more easily appropriated. The IFAR data allow a more detailed examination of how the effect of humanitarian food aid on violence conflict changes when that food aid is more easily stolen by armed groups.

I use two proxies for the ease of expropriation: the number of implementing partners and the cost per ton of food aid. Implementing partners are the NGOs and INGOs with whom USAID partners to deliver the food aid. Implementing partners manage the 'last mile' delivery and distribution of food commodities. As food aid is spread between more implementing partners, there are more points at which food aid could be stolen: more distribution centers, more supply hubs, more trucks. Similarly, cost per ton of food aid increases with the difficulty in transporting food aid within countries.[12] Transporting food within the DRC will be costlier than transporting it with Senegal, due to the greater distances and rougher terrain. Elevation will also increase the cost per ton of food aid. Both elevation and terrain cover provide opportunities to ambush food shipments, suggesting that appropriating food aid will be easier in countries with a higher cost per ton of food aid.

On the other hand, the cost per ton is likely endogenous to the risk of expropriation. USAID and its implementing partners are concerned about the risk of expropriation, so they take increased precautions in areas where such theft is likely. As such, in ongoing conflicts a high risk of expropriation could increase the cost per ton of food aid. This dynamic could explain why the average ITSH per ton of humanitarian food aid is $381 in Kenya but $847 in neighboring Somalia. The former is larger, so food aid may travel to greater areas, but the need for protection is likely smaller.

Table 4 shows the relationship between humanitarian food aid and violent conflict when the former is interacted with two proxies for the ease of appropriation: the number of implementing partners and the cost per ton of food aid. If food aid increases violent conflict because rebels appropriate it, one might expect a positive and significant interaction effect between ease of appropriation and violent conflict. Table 4 shows no such results. The effect of humanitarian food aid on violent conflict does not appear to increase as food aid becomes easier to appropriate. Moreover, the potential endogeneity between the cost per ton of humanitarian food aid and the ease of expropriation

[12] I use cost per ton here rather than ITSH (as per table 1) because the latter are broken out in the IFARs only beginning in 2014.

Table 4. Humanitarian food aid, ease of appropriation, and the risk of conflict

	Conflict incidence			
	(1)	(2)	(3)	(4)
Humanitarian food aid (1000MTs)	0.0008	0.0006	0.0002	0.0004
	(0.0005)	(0.0008)	(0.0006)	(0.0009)
Humanitarian food aid * N. of partners	−0.0001	0.0000		
	(0.0001)	(0.0001)		
Humanitarian food aid * Cost per ton			0.0000	0.0000
			(0.0000)	(0.0000)
Nunn and Qian controls	X		X	
Mary and Mishra controls		X		X
Num.Obs.	2334	2054	2326	2047
R2	0.609	0.918	0.603	0.917

Note: Models 1 and 2 interact emergency food aid tonnage with the number of implementing partners across whom the aid was spread. Models 3 and 4 interact emergency food aid tonnage with the cost per ton. The outcome variable is conflict incidence. Estimates are from a linear probability model; standard errors are clustered at the region level. Data sources are listed in Tables A5 and A6. * p < 0.05, ** p < 0.01, *** p < 0.001

should bias these results upwards. Nevertheless, the results are both substantially and statistically insignificant. These results show how focusing on the logistics and details of humanitarian food aid can better unpack specific mechanisms.

5 Conclusion

Despite the challenges enumerated above, USAID distributed 1,315,526 metric tons of food commodities to its humanitarian aid programs around the world in 2019 alone. This paper introduces a new source of highly disaggregated, program-level data which sheds light on humanitarian food assistance. Previous research has suffered from at least one of two data problems. First, not all food aid is humanitarian aid: a substantial portion of US food aid is monetized by local partners to fund development projects. This process complicates simple narratives of insurgents appropriating food aid—how do you appropriate an agricultural extension program? Second, using aid disbursements as a measure of aid received masks systematic differences in how much aid is delivered. Disbursements include transportation costs, which vary with geographic conditions of the country, the size of the food grant, and the conflict status of the country. This imprecision in pre-existing sources of data on humanitarian aid goes a long way towards reconciling disparate results within the preexisting literature.

This paper introduces new data on humanitarian food aid that alleviate both of these problems and shed new light on the relationship between humanitarian aid and civil conflict. Specifically, the IFAR dataset calls into question a number of hypothesized causal relationship between humanitarian food aid and violent conflict (Nunn and Qian 2014; Christian and Barret 2021; Mary and Mishra 2020).

The data introduced by this paper shed light on the complexities of measuring humanitarian food aid. Different measurement strategies have tradeoffs which affect the results obtained by the researcher. This paper clarified these tradeoffs. The IFAR data will help researchers to disentangle the effects of different modalities of humanitarian aid and offer new opportunities for future research.

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

Table A1. Humanitarian Food Aid and Conflict Incidence

	Intrastate conflict				
	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	0.6007	0.6036	0.6215
Panel A: Reduced Form Estimates					
Instrument	0.0000	0.0000	0.0000	-0.0001	0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
R^2	0.5891	0.5893	0.5983	0.6015	0.6193
Panel A: 2SLS Estimates					
Instrumented food aid (1000MTs)	-0.0003	0.0000	0.0009	0.0009	0.0008
	(0.0007)	(0.0000)	(0.0010)	(0.0011)	(0.0013)
R^2	0.5863	0.5842	0.5920	0.5943	0.6137
Panel A: First-Stage Estimates					
Instrument	0.0766	0.0736	0.0746	0.0745	0.0835
	(0.0382)	(0.0356)	(0.0342)	(0.0347)	(0.0437)
Kleibergen-Paap F-statistic	4.0078	4.2610	4.7472	4.6110	3.6523
Number of observations	2540	2540	2334	2334	1909
Country FEs	X	X	X	X	X
Region-year FEs	X	X	X	X	X
US GDP per capita * avg. prob.		X	X	X	X
US democratic pres. * avg. prob.		X	X	X	X
Oil price * avg. prob.		X	X	X	X
Monthly recipient temp. and rainfall			X	X	X
Monthly weather * avg. prob.			X	X	X
Avg. US military aid * avg. prob.				X	X
Avg. US economic aid * avg. prob.				X	X
Avg. cereal imports * year FEs					X
Avg. cereal production * year FEs					X

Note: This table replicates the Table 2 from Nunn and Qian (2014), but exclusively for intrastate wars. Estimates are from a linear probability model. The outcome variable is the probability of a civil war occuring in any given year. Standard errors are clustered at the country level. Data sources are listed in Table A.5

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 A.1 replicates table 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 (2021) 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 A.2 and A.3 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 A.5 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

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

	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)
Decisive victory	−0.686**	−0.619*	−0.650**	−0.707**	−0.743**	−0.708**	−0.637**
	(0.254)	(0.250)	(0.247)	(0.247)	(0.241)	(0.240)	(0.236)
Lootable resources	0.543*	0.558**	0.541**	0.293	0.276	0.196	0.204
	(0.215)	(0.210)	(0.208)	(0.201)	(0.199)	(0.189)	(0.186)
Treaty	−0.370	−0.713*	−0.729*	−0.873**	−0.888**	−0.850**	−1.246***
	(0.357)	(0.333)	(0.337)	(0.327)	(0.329)	(0.329)	(0.288)
Identity war	−0.228	0.031	0.043	0.227	0.218	0.129	0.122
	(0.228)	(0.207)	(0.206)	(0.200)	(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	−0.112	−0.066	−0.067	−0.065	−0.064	−0.071	−0.065
	(0.115)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Democracy	0.070	0.149					
	(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*	0.000*	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	0.433						
	(0.279)						
Former P-5 colony	0.606**						
	(0.230)						
Duration of war	0.009	0.007	0.008	0.011	0.011	0.010	0.005
	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)

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

reports. 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 A.6 lists all countries which appear in the IFAR data and enumerates the number of years in which they received food assistance from USAID.

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

	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)

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

Table A4. Humanitarian food aid and the risk of civil war termination

	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)

Note: This table replicates column 2 of Tables 1 and 2 from Narang (2015). Estimates are from a Cox Proportional Hazards model. Data sources are listed in Table A8. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5. Value of Humanitarian Food Aid and Conflict Incidence

	Intrastate conflict		
	Nunn and Qian	Christian and Barrett	Mary and Mishra
Panel A: OLS Estimates			
Humanitarian food aid (mil. of USD)	0.0009	0.0000	0.0004
	(0.0004)	(0.0003)	(0.0004)
R^2	0.6222	0.7531	0.9175
Panel B: Reduced Form Estimates			
Instrument	-0.0001	-0.0001	0.5128
	(0.0001)	(0.0001)	(1.3945)
R^2	0.5966	0.7504	0.9150
Panel C: 2SLS Estimates			
Instrumented food aid (mil. of USD)	0.0008	-0.0004	0.0002
	(0.0013)	(0.0010)	(0.0015)
R^2	0.6174	0.7604	0.7973
Panel D: First-Stage Estimates			
Instrument	0.0777	0.0608	10.5005
	(0.0404)	(0.0367)	(71.0369)
Kleibergen-Paap F-statistic	3.6994	2.7415	0.0219
Number of observations	1909	1909	2046
Nunn and Qian Controls	X	X	
Unit-specific cubic time trends		X	X
Mary and Mishra Controls			X

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 outcome variable is the probability of a civil war occuring in any given year. Standard errors are clustered at the country level. Data sources are listed in Tables A.5 and A.6

Table A6. Countries represented in the IFAR data

	Years receiving aid			
Country	Emergency	Development	Combined	Any
Afghanistan	23	3	2	25
Albania	3	0	2	5
Algeria	10	0	0	10
Angola	13	5	4	17
Armenia	7	0	1	8
Azerbaijan	8	0	0	8
Bangladesh	9	25	3	28
Benin	0	12	4	16
Bhutan	0	0	2	2
Bolivia	0	14	4	18
Bosnia & Herzegovina	4	0	1	5
Botswana	0	1	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	1	6
Cameroon	13	5	1	18
Cape Verde	0	12	4	16
Central African Republic	16	5	4	25
Chad	18	19	3	28
Colombia	16	0	1	17
Comoros	0	1	2	3
Congo - Brazzaville	12	0	3	15
Congo - Kinshasa	17	11	0	17
Costa Rica	0	2	3	5
Côte d'Ivoire	11	4	3	18
Croatia	0	0	1	1
Djibouti	21	2	1	23
Dominican Republic	1	6	4	10
Ecuador	4	4	2	10
Egypt	0	9	2	11
El Salvador	8	3	3	13
Equatorial Guinea	0	1	0	1
Eritrea	8	8	1	12
Eswatini	2	0	2	4
Ethiopia	25	24	4	29
Gambia	3	11	4	17
Georgia	8	0	1	9
Ghana	0	15	4	19
Guatemala	11	22	4	26

Guinea	10	15	2	18
Guinea-Bissau	2	3	4	9
Guyana	0	3	2	5
Haiti	16	23	4	28
Honduras	8	15	4	20
India	1	16	3	19
Indonesia	7	9	3	14
Iran	0	0	1	1
Iraq	6	0	2	7
Jamaica	0	1	2	3
Jordan	0	2	1	3
Kenya	25	18	4	29
Laos	2	2	1	5
Lebanon	2	0	3	5
Lesotho	3	5	4	11
Liberia	18	13	4	25
Libya	1	0	0	1
Madagascar	11	24	4	28
Malawi	8	18	4	25
Mali	15	10	4	25
Mauritania	15	18	4	28
Mauritius	0	1	3	4
Mexico	0	1	4	5
Mongolia	0	0	1	1
Morocco	0	2	4	6
Mozambique	9	15	4	25
Myanmar (Burma)	4	0	0	4
Namibia	1	0	0	1
Nepal	14	3	2	17
Nicaragua	9	14	4	18
Niger	16	24	4	28
Nigeria	5	0	0	5
North Korea	9	0	0	9
North Macedonia	1	0	1	2
Pakistan	21	7	3	24
Palestinian Territories	16	0	4	20
Panama	0	1	4	5
Paraguay	0	1	2	3
Peru	0	12	4	16
Philippines	5	2	3	10
Russia	3	0	0	3
Rwanda	18	12	2	21
São Tomé & Príncipe	0	2	4	6
Senegal	5	12	3	19
Serbia	2	0	0	2
Sierra Leone	13	14	4	24

Slovenia	0	0	1	1
Somalia	25	0	4	29
South Sudan	9	3	0	9
Sri Lanka	9	5	1	13
Sudan	25	1	4	29
Syria	5	0	0	5
Tajikistan	13	3	0	14
Tanzania	23	4	0	22
Thailand	0	0	1	1
Timor-Leste	5	0	0	5
Togo	0	1	4	5
Tunisia	0	1	0	1
Uganda	25	21	4	29
Yemen	12	6	2	20
Zambia	8	11	1	14
Zimbabwe	14	6	1	15

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 (2021) 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 seperate table for the paper.

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

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 A8. Control variables from Mary and Mishra (2020)

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 A9. Control variables from Narang (2014)

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 A10. Control variables from Narang (2015)

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).