LETTER

REPLY TO PLEWIS, MURARI ET AL., AND DAS:

The suicide–temperature link in India and the evidence of an agricultural channel are robust

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In Carleton (1) I demonstrate that increases in growing-season temperatures in India contribute to rising suicide rates. In secondary analysis, I show correlational evidence of an agricultural channel, in which heat damages crops and crop losses induce suicide. The concerns raised by Murari et al. (2), Das (3), and Plewis (4) have three common features. First, they fail to acknowledge that I quantify the elevated risk of suicide due to the climate, superimposed upon risks from other factors, such as health, religion, or substance abuse, all of which are accounted for nonparametrically. Second, they focus on the agricultural mechanism, such that their implications have no bearing on the primary findings in Carleton (1). Finally, the authors incorrectly claim that many results recovered from data were assumptions made before analysis. Here I respond to each critique. Across all additional tests, the original findings in Carleton (1) remain unaffected, and often are strengthened.

Occupation of Suicide Victims

I use annual state-level records with suicides pooled across occupations (1). Murari et al. (2) and Plewis (4) claim that aggregation across farmers and nonfarmers makes identification of climate effects infeasible, as suicides in nonfarmers are unlikely to be climatically influenced. This claim is erroneous. First, there are many avenues through which nonfarmers may be affected, including food prices and labor market changes (5, 6). Second, a signal originating in a subpopulation can in fact be uncovered in a combined sample. Consider aggregate rates of cigarette smoking and lung cancer in a population. If smoking declines, the population-wide cancer rate may fall, despite nonsmokers' experiencing no change in their cancer likelihood. Similarly, it is possible to uncover a farmer-driven signal in aggregate suicide data. Indeed, if nonfarmers are unaffected by the climate, the average treatment effects uncovered in Carleton (1) represent underestimates of farmer-only effects.

Aggregation of suicides across occupations does not preclude identification of causal climate effects. However, subpopulations may respond differentially, and records including suicide victims' occupations would allow us to test for such heterogeneity. Unfortunately, available data are extremely limited; estimates of farmer-only suicide rates in India cover a short time series with limited spatial extent and error-prone occupational classifications (7, 8). Plewis (7) constructs such estimates for nine states between 1996 and 2011, pairing incomplete data with assumptions, such as the number of farmers per agricultural holding. Acknowledging that these data are limited in quantity and quality, I use Plewis' estimates to formally test whether farmers respond differently to temperature using the seemingly unrelated regression method from Hsiang and Meng (9). The test statistics at the bottom of Table 1 indicate that growing-season temperature effects on suicide rates in the farmer-only data are larger than, but statistically insignificantly different from, original estimates in aggregate data.*

Plewis' second concern (4) is that downward trends in farmer suicide rates shown in Plewis (7) contradict my finding that ~59,000 suicides are attributable to warming (1). This argument is misguided, as trends are affected by many factors unrelated to climate.

*Plewis (7) applies an inflation factor to all suicide records to account for underreporting, which may be one reason why the point estimates from models using those data are an order of magnitude higher than those estimated using the National Crime Records Bureau (NCRB) data.

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Data deposition: Additional details in response to these comments, as well as others, are available at https://osf.io/r3xcv.

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Table 1. Testing for heterogeneity in the effects of temperature on farmer-only and total suicide rates

Variable	Total suicide rate (per 100,000) Thirty-two states 1967–2013	Total suicide rate (per 100,000) Nine states 1996–2011	Farmer suicide rate (per 100,000) Nine states 1996–2011	Farmer suicide rate (per 100,000) Nine states 1996–2011
Growing season				
Degree days below threshold, °C	0.004	0.005	0.052	0.051
	(0.001)	(0.006)	(0.109)	(0.105)
Degree days above threshold, °C	0.008	0.004	0.042	0.034
	(0.003)	(0.006)	(0.032)	(0.030)
Nongrowing season				
Degree days below threshold, °C	−0.002	−0.002	−0.017	−0.022
	(0.001)	(0.002)	(0.036)	(0.031)
Degree days above threshold, °C	0.002	−0.002	−0.025	−0.024
	(0.003)	(0.003)	(0.036)	(0.034)
Observations	1,434	144	288	288
R-squared	0.916	0.977	0.841	0.849
		Testing whether coefficients differ from Carleton (1) using SUR (*P* value)		
Growing season degree days above threshold		0.0172	0.3939	0.5296
All temperature variables		0.1386	0.8387	0.8320

Column 1 shows the benchmark model from Carleton (1). Column 2 restricts the National Crime Records Bureau (NCRB) data to the states and years overlapping with the sample in Plewis (7). In columns 3 and 4, the dependent variables are two different estimates of farmer suicide rates compiled by Plewis (7). The degree days threshold is 25 °C, and all regressions include state fixed effects, year fixed effects, state-specific linear trends, and nonlinear season-specific rainfall controls. Standard errors in column 1 are clustered at the state level, while all other regressions use heteroskedasticity robust standard errors due to the limited number of states included in the regression. Regressions in columns 2–4 are each run simultaneously with the Carleton (1) model using seemingly unrelated regression (SUR); *P*-values on the null hypothesis that coefficients are the same from the two models are shown at the bottom.

Moreover, it is inconsistent with the original analysis. Trends are not used for causal inference in Carleton (1), because there are many unobserved and possibly confounding trending variables. In contrast, Carleton (1) exploits year-to-year deviations in climate, as opposed to long-run trends, to estimate causal effects on suicide. The estimated impact of growing-season temperature is then used to predict suicides under the actual temperature experienced, and under a counterfactual temperature where observed warming trends were removed. The difference between predicted suicides under the actual climate (with warming) and counterfactual climate (without warming) is reported. For details on this method, see Lobell et al. (10) and Carleton and Hsiang (11).

Temperature Exposure

Murari et al. (2) and Das (3) cite a range of literature when claiming that crop damages occur only at temperatures far above 20 °C, the value of the kink point in some degree-day models in Carleton (1). However, studies cited by the authors are repeatedly misquoted. For example, Murari et al. (2) assert that crop-specific temperature thresholds in Luo (12) range from 33 °C to 38 °C; in fact, Luo states that wheat-grain filling declines after 20.7 °C, and rice-grain yield falls after 25 °C (12). Das (3) cites Welch et al. (13) when claiming that temperatures only above 35 °C damage rice, yet Welch et al. (13) use a linear model in maximum temperature, finding a positive effect on rice yield during vegetative and ripening growth phases.

Direct comparison of temperature thresholds across studies is misguided for other reasons. Thresholds can be defined with respect to instantaneous temperature (14), average annual or seasonal temperature (10), daily minimum or maximum temperature (13), or daily average temperature (1), among others. Which temperature variable is used will have important implications for the identified threshold. In particular, analyses using average temperatures are likely to uncover lower thresholds than those using maximum temperatures, by construction. Aggregation across space, time, and crops also complicates cross-study comparisons. If individual plants experience severe damages from instantaneous high temperatures, the response uncovered in a dataset aggregating across large spatial extents (e.g., states), across hours (e.g., daily average temperature), and across crops (e.g., rice and sorghum) is likely to differ from a response generated with higher-resolution data. This is because when crop production is aggregated, each observation represents a

Table 2. Distribution of maximum temperatures within states and districts

Daily average temperature	Average % of area with daily maximum temperature exceeding: 30 °C, %	33 °C, %	35 °C, %	38 °C, %
Aggregated to state level				
17.5–22.5 °C	27	11	6	3
22.5–27.5 °C	35	20	13	7
Aggregated to district level				
17.5–22.5 °C	28	8	3	1
22.5–27.5 °C	40	21	12	5

Percentage values show, for a given range of daily average temperatures aggregated across a state or district, the percent of the state or district's area that experiences a maximum temperature above 30 °C, 33 °C, 35 °C, or 38 °C, on average across all years in the Carleton (1) sample.

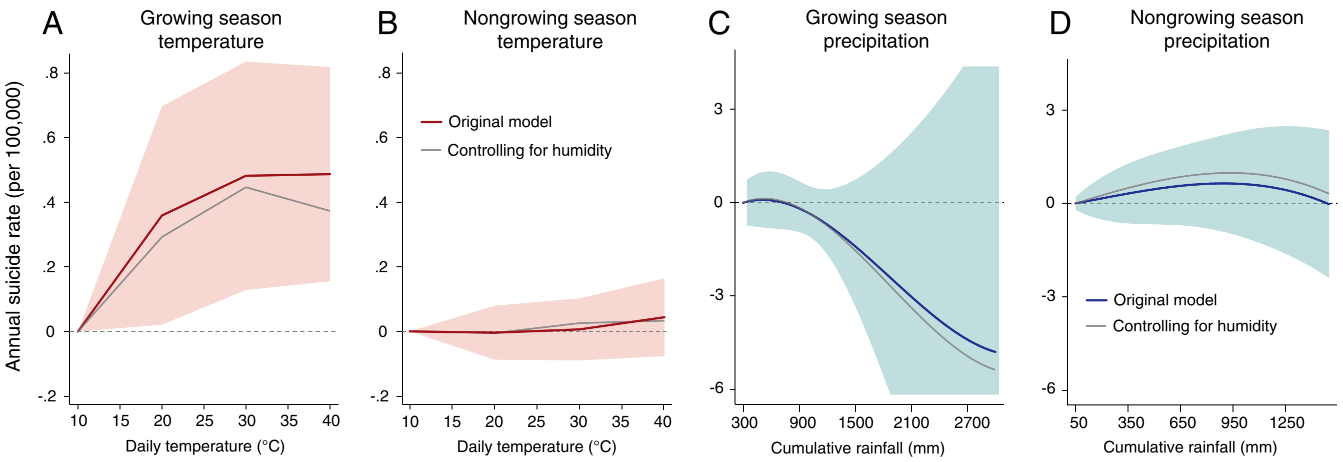

Fig. 1. The impact of including humidity on the effect of season-specific temperature and rainfall on suicide rates. The response of annual suicide rates (deaths per 100,000 people) to growing and nongrowing season temperature (*A* and *B*) and precipitation (*C* and *D*). Red and blue lines show results from a model omitting humidity, while gray lines show results from a model including a quadratic in monthly average specific humidity over the growing and nongrowing seasons. Both regressions include state fixed effects, year fixed effects, and state-specific linear trends. Standard errors are clustered at the state level.

large distribution of crop types experiencing distinct temperatures in different locations. This aggregation effect is detailed in Burke et al. (15).

To use annual state- and district-level outcomes, it was necessary in Carleton (1) to create aggregated indices of temperature. Great care was taken to ensure that valuable information on extremes of the temperature distribution was preserved, by using daily data and taking nonlinear transformations at grid-cell level before aggregating (1, 16). However, with daily average temperatures and coarse resolution climate data, the aggregate climate indices do not fully capture the distribution of diurnal or subgrid-cell temperatures. To demonstrate some of the implications of these approximations, I generated summary statistics of daily maximum temperatures (17) experienced within a state or district on a day when the daily average temperature across that region was ~20 °C or 25 °C. Table 2 shows that on a day when the state-level average temperature is ~25 °C, 35% of that state's area faces a maximum temperature ≥30 °C; 13% experiences a maximum temperature ≥35 °C, on average. Similar values for districts indicate that when regions have average temperatures near 20 °C, significant areas within their

Table 3. Impact of temperature on annual suicide rates and annual log yields under different season definitions

	Suicide rate (per 100,000)			100 × log yield (rupees per ha)		
Variable	Two seasons (all states)	Three seasons (all states)	Three seasons (rabi states)	Two seasons (all states)	Three seasons (all states)	Three seasons (rabi states)
Summer growing season (June–September)						
Degree days below threshold, °C	0.004***	0.003***	0.005	0.012	0.008	−0.057***
	(0.001)	(0.001)	(0.007)	(0.010)	(0.010)	(0.012)
Degree days above threshold, °C	0.008**	0.008**	0.004	−0.026**	−0.025**	−0.085***
	(0.003)	(0.003)	(0.004)	(0.011)	(0.011)	(0.013)
Winter growing season (October–March)						
Degree days below threshold, °C		−0.002*	0.005		0.004	−0.024**
		(0.001)	(0.003)		(0.005)	(0.010)
Degree days above threshold, °C		−0.000	0.004		−0.009	−0.057*
		(0.006)	(0.013)		(0.014)	(0.030)
Nongrowing season (all other months)						
Degree days below threshold, °C	−0.002	0.000	0.000	−0.006*	−0.013***	−0.011
	(0.001)	(0.003)	(0.005)	(0.004)	(0.005)	(0.008)
Degree days above threshold, °C	0.002	0.005	−0.013	0.032***	0.045***	0.055***
	(0.003)	(0.006)	(0.010)	(0.003)	(0.010)	(0.021)
Observations	1,434	1,409	230	11,289	11,006	5,509
R-squared	0.916	0.919	0.901	0.849	0.850	0.870

Columns 1 and 4 use the season definitions in Carleton (1), where the summer growing season is June–September. All other columns add to this summer season a winter (rabi) growing season, composed of October–December of the previous year plus January–March of the current year. In both cases, the nongrowing season is composed of all remaining months. Estimates in columns 3 and 6 include data only from the five states producing over 75% of India's winter wheat crop (Uttar Pradesh, Madhya Pradesh, Punjab, Rajasthan, and Haryana). The degree days threshold is 25 °C, and all regressions are run with state fixed effects, year fixed effects, state-specific linear trends, and nonlinear season-specific rainfall controls. Standard errors are clustered at the state level in columns 1 and 2, and at the district level in columns 4–6. In column 3, heteroskedasticity robust standard errors are estimated due to the limited number of states included in the regression. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

borders experience temperatures exceeding thresholds discussed by Murari et al. (2) and Das (3). Nonetheless, to assuage any remaining concerns, new findings in this reply use a 25 °C threshold.[†]

Growing Seasons

My analysis identifies climate effects in the summer growing season (June–September) and the nongrowing season (all other months) (1). Despite extended discussion in Carleton (1) of this approach, as well as robustness tests, Murari et al. (2) argue that climate during winter should be separately identified from other months, as some crops are grown primarily during this period.

While testing for heterogeneity across three seasons is a reasonable additional analysis, focusing on two seasons is justified and follows existing research. First, note that a multicrop yield index was used in Carleton (1) to capture generalized agricultural losses from climate events, instead of crop-specific yield, as is appropriate in analyses focusing on individual crops. In this multicrop index, four of six crops are predominately grown during summer, including rice, India's staple grain. Of the remaining two, sugarcane and wheat, only wheat is grown primarily during winter. Second, it is standard to focus on the summer season due to the agricultural importance of the southwestern monsoon (18, 19). While Murari et al. (2) claim that previous research demonstrates yields are most sensitive to winter temperature, the reference cited does not directly estimate yield losses; in fact, Lobell et al. (20) investigate the impact of climate on the duration of the growing season for a single winter crop, wheat.

To assess whether winter months exhibit differential effects, here I estimated a three-season model with June–September as the summer growing season, October–March as the winter growing season, and all remaining months as the nongrowing season.[‡] Table 3 shows two key findings. First, summer temperature impacts are virtually unchanged by the inclusion of a winter season (columns 1, 2, 4, and 5). Second, when the sample is limited to states where wheat is a principal crop, the effects of temperature become damaging during winter months as well (columns 3 and 6). Thus, the central finding of Carleton (1) is unaffected, and the result that winter temperatures influence suicides and yields within locations relying on winter crops provides further evidence that the mechanism through which temperature impacts suicides is plausibly crop loss (1).

Humidity and Data Quality

Including humidity in the main regression in Carleton (1) has a small and statistically indistinguishable effect on suicide–climate responses (Fig. 1), contrary to the hypothesis in Das (3). Measurement error is extremely unlikely to drive the main results in Carleton (1) and data inconsistencies discussed in Murari et al. (2) apply only to occupational classifications, which are not used in Carleton (1).

[†]Extending the threshold beyond this level would result in too little variation: 36% of the observations in the state-level panel dataset have zero growing season degree days above 30 °C, making such a threshold statistically intractable.

[‡]Because winter crops harvested in year t are planted in year $t - 1$, I used October–December of the previous year plus January–March of the present year to define the winter season.

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