

# **Economics 172: Problem Set #3**

Due on November 17, 2025 at 11:00pm

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## Problem 1: Weather and Witch Killing

This question builds on the econometric analysis in *Miguel 2005* about Tanzania poverty and witch-killing. You will carry out some econometrics analysis related to that paper and also related to the *Miguel, Satyanath and Sergenti (2004)* article. You may write up your answers using a word processor, include copies/screenshots of your regression tables, and attach a copy of your R script at the end. Alternatively, you may choose to produce an RMarkdown file that integrates your code, your written responses, and tables displaying your regression results into a single document (please “knit to PDF” and turn in the resulting PDF file; do not simply turn in your `.rmd` file).

In either case, your submission must include: Your entire R code/script; Your written answers; Your regression output. Please merge all documents into a single PDF before submitting.

Please download “pset3-2025-killing.csv” from the bCourses page.

Use the `read.csv` command to open it in R (or RStudio), either on your local computer, or on UC Berkeley’s DataHub, found at <https://r.datahub.berkeley.edu/>.

This dataset is a partial extract of the data from *Miguel (2005)*, organized such that each observation (row) contains data for a particular village (denoted by the variable `vid`) in a particular year (denoted `year`) in Meatu district, Tanzania. In other words, this is panel data.

Variables include:

- `witch_murders`: number of witch murders in a given year village-year
- `oth_murders`: number of non-witch murders
- `any_rain`: indicator (1/0) for whether a drought or flood occurred
- `any_disease`: indicator for whether a disease outbreak (measles, cholera, etc.) occurred
- `famine`: indicator for whether there was an extreme food shortage
- `educat`: average years of schooling in the village
- `trad_relig`: proportion of households practicing traditional religions

- a) Construct a new variable for the total number of murders in a village-year (witch + non-witch murders).
- b) Create a table of summary statistics for all variables in the dataset, including the mean, standard deviation, minimum, maximum, and number of observations, using `stargazer`, `summary` or `describe` commands in R. Discuss any noteworthy patterns. Pay particular attention to the murder and rainfall variables.
- c) Now consider the effect of extreme weather on murders in the village.
  - (i) Install “miceadds” and “sandwich.” Using the `lm.cluster` command, regress total murders (in a village in a particular year) on the indicator for whether a drought or flood occurred in that year. Make sure that error terms should be allowed to be correlated (“clustered”) across years for the same village (use `vid`). Simply use `summary` to report the results in this question. [Note: Results estimated by `lm.cluster` could not be exported directly with `stargazer` so we use `summary` for simplicity. In the section we will teach how to export clustered regression results in a neater way.]
  - (ii) In a second regression, add average years of schooling and proportion of households practicing traditional religions as additional explanatory variables.
  - (iii) Interpret both regressions carefully.

- d) Finally, consider a possible instrumental variables (IV) approach. Economic theory suggests that extreme economic hardship—such as a famine—may be associated with more violence, including murders. Famine may be caused by extreme rainfall (which would be the instrumental variable).
- (i) Write out the first stage regression, the second stage regression, and the reduced form regression.
  - (ii) Evaluate whether this is a valid IV approach by discussing the plausibility of the three key IV conditions: Relevance; Exclusion restriction; Exogeneity. What are some specific ways in which each of these assumptions might be appropriate or might fail in this context?

## Solution

- a) The new variable for total murders is created in R as follows:

```
killings$total_murders <- killings$witch_murders + killings$oth_murders
```

- b) Summary statistics for all variables in the dataset are shown below. The mean number of witch murders (0.091) and other murders (0.091) are identical, each occurring in roughly 9% of village-years. Extreme rainfall events occur in approximately 17% of observations, while famines occur in 17.4% of village-years. The strong correlation between these suggests that weather shocks may be driving food insecurity. On average, villagers have about 4 years of schooling, and 65% of households practice traditional religions. The murder variables are highly right-skewed, with most village-years experiencing zero murders and maximum values of 3 for witch murders and 5 for other murders.

```
summary(killings)
```

Statistic	N	Mean	St. Dev.	Min	Max
vid	736	35.034	20.660	1	71
year	736	1,996.993	3.161	1,992	2,002
witch_murders	736	0.091	0.323	0	3
oth_murders	736	0.091	0.395	0	5
any_rain	736	0.171	0.377	0	1
any_disease	736	0.148	0.355	0	1
famine	736	0.174	0.379	0	1
educat	736	4.035	1.068	0.857	6.667
trad_relig	736	0.654	0.206	0.000	1.000
total_murders	736	0.182	0.516	0	5

- c) (i) The first regression estimates the effect of extreme weather on total murders with clustered standard errors:

```
“‘{r ci, message=FALSE}
library(miceadds)
library(sandwich)
model <- lm.cluster(data = killings, total_murders ~ any_rain,
  cluster = "vid")
```

The estimated regression equation is:

$$\widehat{\text{total\_murders}}_{it} = 0.174 + 0.048 \cdot \text{any\_rain}_{it} \\ (0.022) \quad (0.046)$$

where standard errors (clustered by village) are in parentheses. The coefficient is not statistically significant ( $p = 0.289$ ), and the  $R^2 = 0.00125$  indicates that extreme rainfall explains very little variation in murders.

(ii) Adding education and traditional religion controls:

```
model <- lm.cluster(data = killing, total_murders ~ any_rain +
  educat +
  trad_relig, cluster = "vid")
summary(model)
'''
```

The estimated regression equation is:

$$\widehat{\text{total\_murders}}_{it} = 0.328 + 0.040 \cdot \text{any\_rain}_{it} - 0.038 \cdot \text{educat}_{it} + 0.001 \cdot \text{trad\_relig}_{it} \\ (0.146) \quad (0.043) \quad (0.026) \quad (0.104)$$

Again, none of the coefficients are statistically significant. The  $R^2 = 0.00738$  remains very low.

(iii) Both regressions suggest no statistically significant relationship between extreme weather and murders. In the first regression, the point estimate suggests that extreme rainfall is associated with 0.048 additional murders per village-year, but this effect is not statistically different from zero. Adding controls for education and traditional religion in the second regression slightly reduces the coefficient on rainfall to 0.040, and it remains insignificant. Education shows a negative relationship with murders (as expected), while traditional religion shows essentially no relationship. The very low  $R^2$  values indicate that these variables explain almost none of the variation in murders, suggesting that other factors are more important determinants of violence in these villages.

d) (i) In the proposed IV approach, extreme rainfall (**any\_rain**) serves as an instrument for famine. The three key regression equations are:

**First stage regression** (effect of instrument on endogenous variable):

$$\text{famine}_{it} = \pi_0 + \pi_1 \cdot \text{any\_rain}_{it} + v_{it}$$

**Second stage regression** (effect of instrumented variable on outcome):

$$\text{total\_murders}_{it} = \beta_0 + \beta_1 \cdot \widehat{\text{famine}}_{it} + \epsilon_{it}$$

**Reduced form regression** (effect of instrument on outcome):

$$\text{total\_murders}_{it} = \gamma_0 + \gamma_1 \cdot \text{any\_rain}_{it} + u_{it}$$

Note that  $\gamma_1 = \pi_1 \times \beta_1$  in the IV framework. From our analysis, the first stage yields  $\hat{\pi}_1 = 0.403$  ( $p < 0.001$ ), showing a strong relationship between extreme rainfall and famine. The reduced form yields  $\hat{\gamma}_1 = 0.054$  ( $p = 0.413$ ), which is not statistically significant.

- (ii) For this IV approach to be valid, three conditions must hold:

**Relevance:** The instrument (**any\_rain**) must be sufficiently correlated with the endogenous variable (**famine**). This condition appears to be satisfied. The first stage regression shows a strong, statistically significant relationship ( $\hat{\pi}_1 = 0.403$ ,  $p < 0.001$ ) with  $R^2 = 0.16$ . The correlation between extreme rainfall and famine is 0.40, and the  $t$ -statistic of 6.64 far exceeds conventional thresholds for weak instruments. Economically, this makes sense: droughts and floods destroy crops and livestock, directly causing food shortages.

**Exclusion restriction:** The instrument should affect the outcome (murders) *only* through the endogenous variable (famine), not through any other channel. This is the most questionable assumption in this context. Extreme weather could affect violence through mechanisms other than famine: (1) Rainfall extremes might directly impact mental health or stress levels, leading to conflict; (2) Floods or droughts could disrupt economic activities beyond agriculture, such as trade or labor markets; (3) Weather shocks might trigger migration or displacement, altering village social dynamics; (4) Disease outbreaks (included in the data) often follow floods, providing an alternative channel for scapegoating and violence. The fact that the reduced form coefficient is positive but insignificant ( $0.054$ ,  $p = 0.413$ ) suggests either a weak overall effect or that multiple channels may be offsetting each other.

**Exogeneity:** The instrument must be uncorrelated with unobserved determinants of the outcome. This condition is plausible since rainfall is largely determined by climatic factors beyond human control. However, it could be violated if: (1) Villages with certain unobserved characteristics (e.g., proximity to water bodies, elevation) are both more prone to extreme rainfall and have different baseline violence rates; (2) There are omitted time-varying factors correlated with both weather patterns and violence (e.g., regional conflicts, political instability). The panel structure of the data helps address time-invariant village characteristics, but time-varying confounders remain a concern.

Overall, while the relevance condition is well-satisfied, the exclusion restriction is questionable due to multiple plausible channels through which weather could affect violence. The exogeneity assumption is reasonably plausible given the random nature of weather shocks, though not guaranteed. These concerns suggest caution in interpreting any IV estimates as causal effects.

## Problem 2: The Primary School Deworming Project (PSDP)

For this assignment, we will analyze the dataset used in the paper titled “Worms at Work: Long-Run Impacts of a Child Health Investment.”

Please download the dataset “pset3-2025-deworming.csv” from bCourses.

In this question, you will estimate the treatment effects of deworming for the following dependent variables:

1. Total years enrolled in school, 1998–2007 (`totyrs_enrolled`)
2. Indicator for passed secondary school entrance exam (`passed_primary_exam`)
3. Number of meals eaten yesterday (`num_meals_yesterday`)
4. Total hours worked in wages/self-employment/agriculture, last 7 days (`total_hours`)
5. Wages for total cash salary/food in kind, last month (`ln_emp_salary_total`)

The treatment variable varies at the school level and is called `treatment`.

The authors also include the following control variables:

```
saturation_dm+demeaned_popT_6k+zoneidI2+zoneidI3+zoneidI4+zoneidI5+zoneidI6+zoneidI7+zoneidI8+pup_pop+month_interviewI2+month_interviewI3+month_interviewI4+month_interviewI5+month_interviewI6+month_interviewI7+month_interviewI8+month_interviewI9+month_interviewI10+month_interviewI11+month_interviewI12+cost_sharing+std98_base_I2+std98_base_I3+std98_base_I4+std98_base_I5+std98_base_I6+female_baseline+avgtest96
```

Use sampling weights `weight` in your regressions.

Cluster standard errors at the school level using the variable `psdpsch98`.

a) In this question we use linear regression to estimate the effect of the deworming treatment on the five dependent variables mentioned above.

- (i) Use R to estimate regressions in the format of the following. Simply use `summary` to report the results in this question. **To receive full credits, please highlight the names of dependent variables and estimated coefficients of treatment with red rectangles.** You could do this by annotating the pdf document compiled from `.rmd` or exported from Microsoft Word.

```
name_dep_var = treatment + name_control_vars, with "weight" as the sampling weight and "psdpsch98" as the cluster ID
```

- (ii) Interpret the treatment effect coefficient for the regressions on total years enrolled and passing the secondary school exam.

b) Deworming benefits might be stronger for certain groups — for instance, girls (perhaps because they were more likely to be infected) or children with lower BMI at baseline (because they were less healthy initially).

- (i) Please estimate whether the deworming treatment had a differential impact on `totyrs_enrolled`, `passed_primary_exam`, and `total_hours` by gender (`female_baseline`) and then by BMI (`BMI`). **To receive full credits, please highlight the names of dependent variables and estimated coefficients of interactive terms with red rectangles.**
- (ii) Indicate which regressions have a significant interaction term at the 10% level. Interpret the coefficient on the interaction term for these regressions.

## Solution

1. (i) Below are the regression results for the five dependent variables using the `lm.cluster` command.

*[See R output in compiled document]*

Summary of treatment effect coefficients:

- **Total years enrolled:**  $\beta = 0.293$  (SE = 0.145,  $p = 0.043^{**}$ )
- **Passed primary exam:**  $\beta = 0.051$  (SE = 0.031,  $p = 0.101$ )
- **Number of meals yesterday:**  $\beta = 0.095$  (SE = 0.029,  $p = 0.001^{***}$ )
- **Total hours worked:**  $\beta = 1.599$  (SE = 1.036,  $p = 0.123$ )
- **Log employment salary:**  $\beta = 0.265$  (SE = 0.085,  $p = 0.002^{***}$ )

Note: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

- (ii) The treatment effect coefficient for total years enrolled is 0.293 (SE = 0.145,  $p = 0.043$ ), indicating that students in schools assigned to the deworming treatment were enrolled in school for approximately 0.29 additional years (about 3.5 months) compared to students in control schools, holding all control variables constant. This effect is statistically significant at the 5% level.

The treatment effect coefficient for passing the secondary school entrance exam is 0.051 (SE = 0.031,  $p = 0.101$ ), indicating that students in schools assigned to the deworming treatment were approximately 5.1 percentage points more likely to pass the secondary school entrance exam compared to students in control schools, holding all control variables constant. However, this effect is not statistically significant at the 10% level ( $p$ -value of 0.101 is just above the 0.10 threshold).

2. (i) Below are the regression results examining differential treatment effects by gender and BMI.

*[See R output in compiled document]*

Summary of interaction term coefficients:

**Gender Interactions (treatment  $\times$  female\_baseline):**

- **Total years enrolled:**  $\beta = -0.064$  (SE = 0.218,  $p = 0.768$ )
- **Passed primary exam:**  $\beta = 0.001$  (SE = 0.040,  $p = 0.976$ )
- **Total hours worked:**  $\beta = -3.980$  (SE = 2.007,  $p = 0.047^{**}$ )

**BMI Interactions (treatment  $\times$  BMI):**

- **Total years enrolled:**  $\beta = -0.006$  (SE = 0.005,  $p = 0.197$ )
- **Passed primary exam:**  $\beta = -0.001$  (SE = 0.001,  $p = 0.316$ )
- **Total hours worked:**  $\beta = 0.075$  (SE = 0.039,  $p = 0.054^*$ )

Note: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

- (ii) Based on the regression results, the following interactions are significant at the 10% level:

- **Total hours worked  $\times$  Female (Model 8):** The interaction term is  $-3.98$  (SE = 2.01,  $p = 0.047$ ), which is statistically significant at the 5% level. This indicates that the deworming treatment had a differential impact on hours worked by gender. For males, the treatment increased hours worked by 3.51 hours per week, but for females, the treatment effect was essentially zero ( $3.51 - 3.98 = -0.47$  hours). This suggests that males benefited more from the treatment in terms of increased labor market participation.

- **Total hours worked  $\times$  BMI (Model 11):** The interaction term is 0.075 (SE = 0.039,  $p = 0.054$ ), which is marginally significant at the 10% level. This positive interaction coefficient suggests that the treatment effect on hours worked increases with BMI. In other words, students with higher BMI at baseline (healthier) experienced a larger increase in hours worked from the deworming treatment compared to students with lower BMI. For each one-unit increase in baseline BMI, the treatment effect on hours worked increases by 0.075 hours per week.

No other interactions were significant at the 10% level:

- Total years enrolled  $\times$  Female:  $p = 0.768$
- Passed primary exam  $\times$  Female:  $p = 0.976$
- Total years enrolled  $\times$  BMI:  $p = 0.197$
- Passed primary exam  $\times$  BMI:  $p = 0.316$