Unsafe water and children's development

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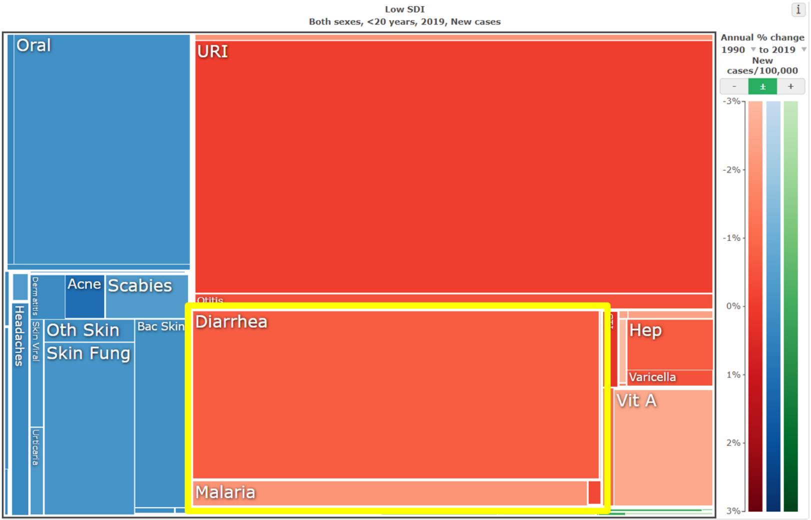
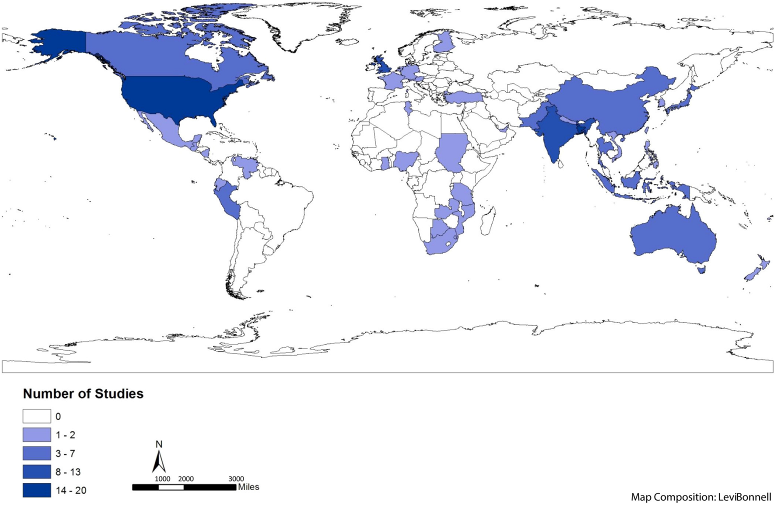
Disease burden in low-income countries (incidence rates)



(Institute for Health Metrics and Evaluation, 2022)

Evidence does not reflect disease burden

- Existing studies on climate risk factors of diarrhoeal diseases (Levy et al., 2016)



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  - Construct a nation-wide hydrological model that simulates *stagnant water pools* across Tanzania
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- Climate change projected to have a dramatic impact on magnitude and frequence: 200% increase with 2°C of warming
- Households and policymakers largely unaware of this (dynamic) risk factor

Contribution and previous literature

- Geographic determinants of development (Alsan, 2015; Easterly and Levine, 2003; Gallup and Sachs, 2000; Nunn and Puga, 2012)
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  - **Lack of evidence from low-income countries**, mostly correlational
- Implications of climate change for public health (Li et al, 2021, Carleton et al., 2022)
  - **WBD are especially sensitive to climate change** - may increase by 200% or more

Waterborne diseases and stagnant water

Doctors warn of possible outbreak of water-borne diseases

Health department rejects news of an epidemic, says all is well

Sameer Mandhro | August 09, 2019

Waterborne diseases, typhoid, cholera, malaria and cases of snakebite usually increase in monsoon due to stagnant water. PHOTO: SAME

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  - Short-run: Diarrhea, stomach pain, vomiting
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- Stagnant water is a main transmission way of these pathogens
  - Enables exponential growth of bacteria and other pathogens (biofilms)
- Fecal-oral channel
  - Contaminated water spread to other water sources through human waste
  - Strong link to water, sanitation and hygiene (WASH) practices

Data: Outcomes and unit of observation

- Health: Demographic and Health Surveys 1999, 2010, 2015
  - Children age 0-4
  - Short-term health issues: Diarrhea, Fever
  - Anthropometric: Height-for-age, Weight-for-age
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  - Child and household characteristics
- Learning: Uwezo Surveys 2011, 2013, 2014, 2015, 2017
  - Children age 6-16
  - Test scores in Mathematics, English, Kiswahili
  - Child and household characteristics

Constructing the treatment variable

- We build a hydrodynamic model for all of Tanzania (90 m)

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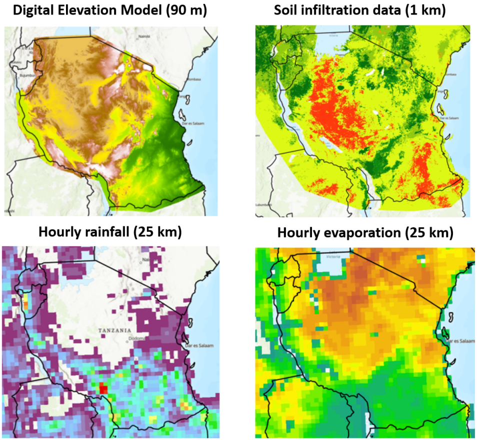
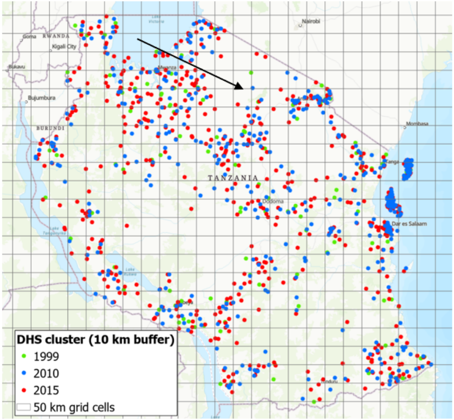
Inputs:

1. Elevation plus rainfall
2. Account for Soil infiltration
3. Account for evaporation
4. Remove flowing water and permanent bodies of water

Methodology details



Unit of treatment



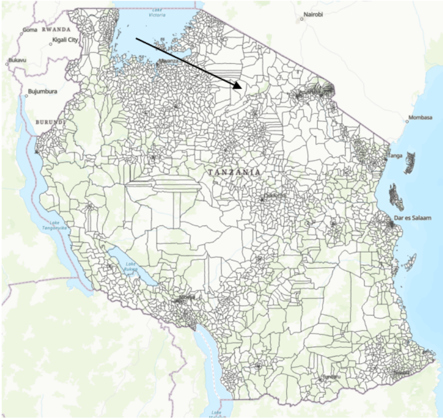


Figure: DHS clusters and gridcells (Left). Uwezo wards (Right)

Output: WBD Potential

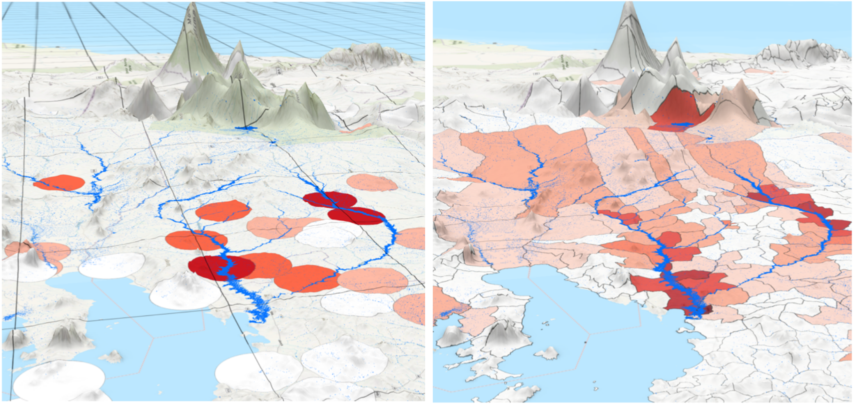


Figure: Treatment with DHS clusters (Left) or Uwezo wards (Right)

Model specification: TWFE

$$Y_{imwy} = \alpha^1_w + \alpha^2_y + \alpha^3_m + \delta S_{wy} + \gamma R_{wy} + X'_{iwy}\beta + \varepsilon_{iwy} \quad (1)$$

- **Treatment**: δS_{wy} – continuous measure of WBD potential in ward w year y in the last 8 weeks relative to the household's date of survey
- δ is our coefficient of interest
- α^1_w, α^2_y and α^3_m capture ward, year and calendar month FE.
- R_{wy} captures local rainfall.
- Covariates in X'_{iwy} include wealth index, child's age and gender, mother's age and education
- Cluster at ward level (Abadie et al., 2017)

Validating the treatment variable

- We validate the measure using reported proximity to nearest surface water source (time-dependent)
  - WBDP predicts proximity to nearest surface water source Link
- Ongoing work: validatation with satellite data
  - Issues with missing data – increase in cloud coverage during the wet season
  - For non-missing data, find positive correlation though relatively weak (0.15)

Effects on child health

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Health and physical outcomes					
	WBD		Other disorders			
	Diarrhoea	W.Age	Fever	Cough	Anemia	Height
WBD Potential	0.275**	-8.192	-0.0499	-0.0587	0.0722	27.35
	(0.113)	(6.244)	(0.140)	(0.144)	(0.0961)	(23.33)
Mean DV	0.13	88.49	0.22	0.21	0.40	92.12
Obs.	15,956	15,021	16,016	16,021	16,085	15,550
Clusters	242	242	242	242	242	242

Effects on child health – by rehydration source

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	Panel B. Health and water					
	Diarrhoea				Fever	
	No Breastf	Breastfeeds	Not water	Water	Not water	Water
WBD Potential	0.506***	0.0844	-0.0822	0.300**	0.130	-0.0719
	(0.152)	(0.135)	(0.202)	(0.121)	(0.391)	(0.235)
Mean DV	0.11	0.14	0.13	0.13	0.22	0.22
Obs.	6,317	9,637	2,089	8,897	2,089	8,912
Clusters	241	241	185	240	185	240

Heterogeneity by access to improved sanitation and drinking water

	(1)	(2)	(3)
		Dependent: Diarrhoea	
Sample:	All	Urban	Rural
WBDP	0.268	1.133***	0.252
	(0.205)	(0.310)	(0.272)
WBDP × sanitation ladder	-0.227***	-0.358**	-0.157**
	(0.072)	(0.136)	(0.093)
WBDP × improved water	-0.162	-0.938***	0.060
	(0.174)	(0.282)	(0.272)
Obs.	11,939	2,880	9,059
Clusters	237	97	230

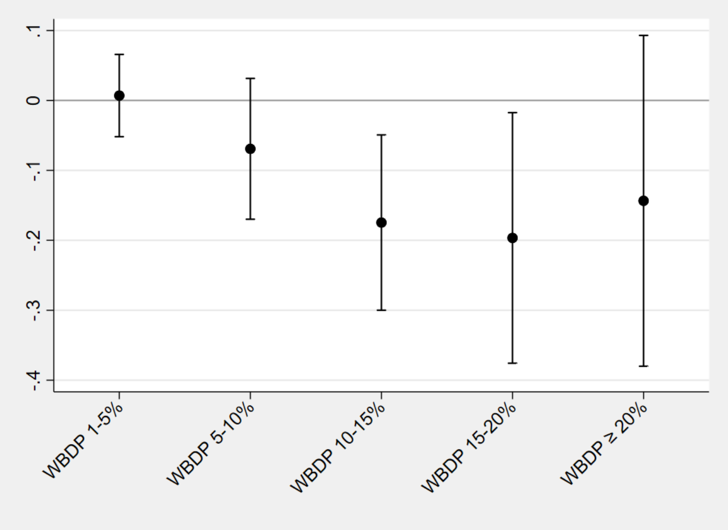
Effects on children's learning

Effects on children's learning

	(1)	(2)	(3)
		Dependent: Test score (std)	
WBD potential ∼(0,1)	-0.632**	-0.687**	-0.716**
	(0.320)	(0.315)	(0.316)
Local rain (cm)			0.00318***
			(0.00118)
Obs.	368,493	368,493	368,444
Clusters	3,842	3,842	3,842
Indv controls:		✓	✓

- DV is a standardised test score average from English, Maths and Swahili
- Indv controls include child gender, age, mother's age, mother's education, household wealth index
- **Interpretation**: 10% shock of WBD Potential reduce test scores by 7% of a standard deviation
- Sensitivity to model specification Link

Non-linear treatment effects?



Heterogeneity

- Effects larger for younger children Link
- No gender differences
- Effects increase with population density, high temperatures and a dry climate Link
  - Consistent with public health literature (Levy et al., 2016)

Robustness checks

- Using a binary treatment indicator (below/above 5 %) Link
- Choice of cutoff value (2-20%) for binary treatment Link
- Timing of treatment Link
- Number of weeks in look-back period Link
- Heterogeneous and dynamic treatment effects Link
- Quadratic term to capture nonlinear effects Link
- Placebo-test 1: No effect of treatment post-test date Link
- Placebo-test 2: No effect of WBD Potential on test scores when randomising treatment within ward Link
- Robustness to spatial correlation and non-random exposure Link
- Sensitivity to model specification Link
- Pretrends Link

Mechanisms and long-run effects

- The effect likely runs partly through school absence
- Even small absence can lead to large long-term effects (Cattan et al., 2023)
- Our coefficient on absence roughly 50 % of diarrhea coefficient (DHS) Link
- Temperature has a big impact: in warm wards ($> 24°C$) the effect size is 4x higher Link

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- What about the long run?
- Suggestive evidence that short-term shocks in the past 1-6 years "add up" Link
- Preliminary findings show similar effects for *current grade*

Alternative explanations

- Floods
  - Only look at *stagnant water*
  - No effects in low-temperature wards
  - Effects still at small magnitudes they quickly saturate
- Malaria
  - Use malaria incidence rate in 2010 (% children with Malaria parasite)
  - Larger effect in *low*-incidence areas
- Child labor(-) / Income(+)
  - Similar effects for farmers vs non-farmers and urban vs rural
  - Crops typically planted in November-January after the first rains - similar effects in other months
- Migration and anticipation
  - Anticipation unlikely for short-term effects (no warning system)
  - Find only small and *negative* effects of exposure on migration (TZA 2012 census)

Impacts of climate change

- Increased frequency of intense rainfall $\rightarrow$ increased frequency of stagnant water
- Increased temperature $\rightarrow$ greater effect size
- We compound the effects: $frequency \times magnitude$ using latest climate projections for East Africa (Ayugi et al., 2021) and find very large multiplicative effects:

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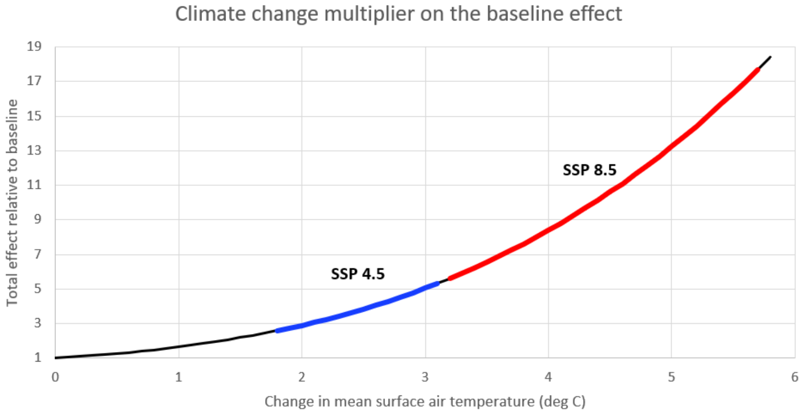

Conclusion

- We develop a novel measure of exposure to unsafe water: *waterborne disease potential (WBDP)* – and study its effect on children's health and learning
- Main take-away:
  - **Findings**: Increased diarrhea incidence and reduced test scores
  - **Policy implications**:
    - Targeted high-quality sanitation and water investments > Large-scale low-quality investments
    - Targeted oral rehydration treatments, hand soap, chlorine tablets, information provision...
    - Short-range forecasts and climate change adaptation

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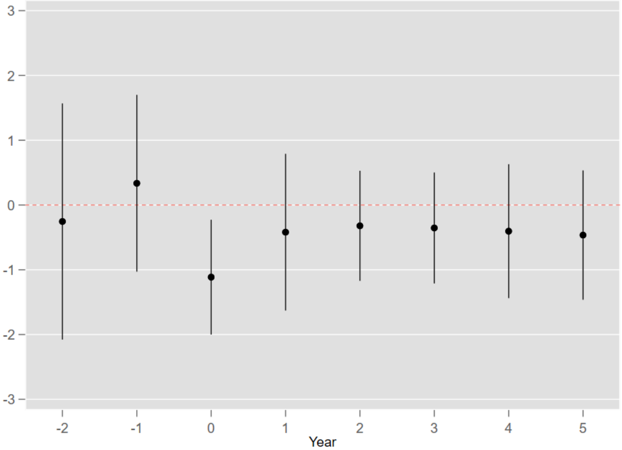
    - Short-range forecasts and climate change adaptation
- Future work:
  - Long-term effects and early-life shocks
  - Further validation of the model with reported historical floods and outbreaks
  - Combine with NGO data on past sanitation investments

Bonus slide

- Preliminary results from an early-life shocks analysis (Household FE specification)



That's all.

Thank you!

Steve Berggreen

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Pretrends

- Few pre-treatment years
- General problem of pre-trend testing Roth, 2022
- We follow Bilinksi and Hatfield, 2019 who propose an alternative:
  - Estimate model under parallel trends assumption
  - Include difference in linear trends (allow for different trends)
  - Report difference in coefficient - is the difference “large”?
  - Our setup: ward-specific linear time trends

Pretrends

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Dependent: Test score (std)					
WBD potential	-1.390***	-1.254***	-0.934***	-0.660**	-0.647**	-0.742**	-0.791**	-1.040***
	(0.280)	(0.221)	(0.334)	(0.324)	(0.319)	(0.315)	(0.345)	(0.351)
Obs.	368,446	368,446	368,444	368,444	368,444	368,444	368,444	368,444
Clusters	3,844	3,844	3,842	3,842	3,842	3,842	3,842	3,842
Covs		✓				✓	✓	✓
Ward FE			✓	✓	✓	✓	✓	✓
Wave FE				✓	✓	✓	✓	✓
Month FE					✓	✓	✓	✓
District $\times$ Wave FE							✓	
Ward-specific linear trends								✓

Robustness to heterogenous and dynamic treatment effects

- Heterogenous treatment effects (de Chaisemartin and D'Haultfoeuille, 2020)
- Robustness to dynamic effects (de Chaisemartin and D'Haultfoeuille, 2021)
- Binary treatment (cutoff: 5 %)

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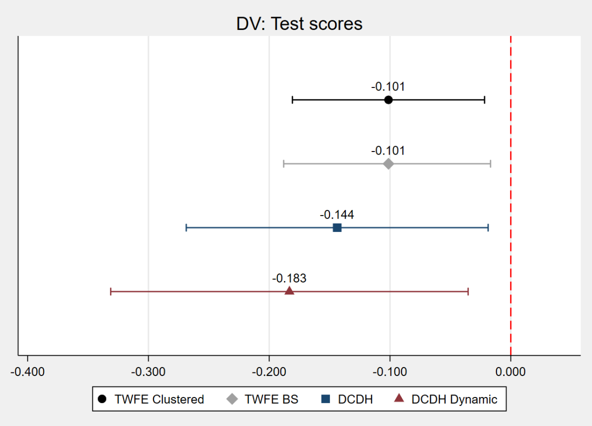

Robustness to spatial correlation and non-random exposure

- Weather instruments suffer from spatial correlation, do not follow admin boundaries (Cooperman, 2017)
- Non-random exposure to exogenous shocks (Borusyak and Hull, 2022)
- Randomization inference: data-driven method to obtain distribution of point-estimates

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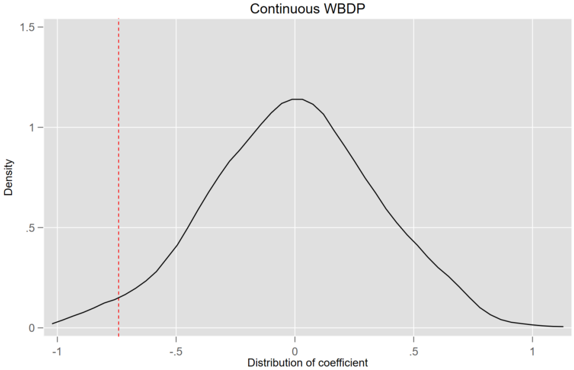
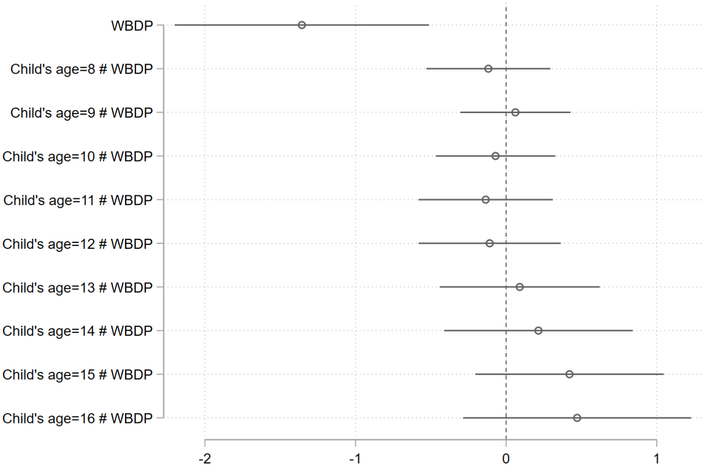
- Randomization inference: data-driven method to obtain distribution of point-estimates
- P-value: $0.02 \rightarrow 0.03$



Age heterogeneity



Heterogeneity by climate

- Split the sample by:
  - Median temperature in the past two weeks ($24.7°C$)
  - Median rainfall in the prior two months ($8\ mm$)

	(1)	(2)	(3)	(4)
	Dependent: Mean test score			
Sample:	Low temp.	High temp.	Dry before	Rainy before
WBD Potential	0.131	-1.128***	-1.064**	-0.375
	(0.442)	(0.403)	(0.429)	(0.692)
Obs.	182,614	185,830	182,766	184,812
Clusters	2,166	2,649	3,141	2,422

Sensitivity to model specification and FE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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Wave FE				✓	✓	✓	✓	✓
Month FE					✓	✓	✓	✓
District × Wave FE							✓	
Ward-specific linear trends								✓

Back

Robustness to including local rain

	(1) All	(2) Dry	(3) Rainy
	Panel A. Dependent: WBD Potential		
Local precipitation (cm)	0.00102**	0.00355**	-0.000499*
	(0.000413)	(0.00172)	(0.000261)
Mean precip (cm/2 weeks)	0.44	0.34	0.53
Obs.	7,240	3,648	3,588
Clusters	2,558	1,319	1,238
	Panel B. Dependent: Test scores		
WBD potential	-0.716**	-0.831**	-0.0209
	(0.314)	(0.348)	(0.734)
Obs.	368,444	178,449	189,995
Clusters	3,842	1,669	2,173
	Panel C. Dependent: Test scores		
Local precipitation (cm)	0.0310***	-0.0357	0.0401***
	(0.0118)	(0.0234)	(0.0135)
Obs.	368,444	178,449	189,995
Clusters	3,842	1,669	2,173
	Panel D. Dependent: Test scores		
WBD potential	-0.742**	-0.812**	-0.00542
	(0.315)	(0.349)	(0.729)
Local precipitation (cm)	0.00318***	-0.00334	0.00401***
	(0.00117)	(0.00235)	(0.00135)
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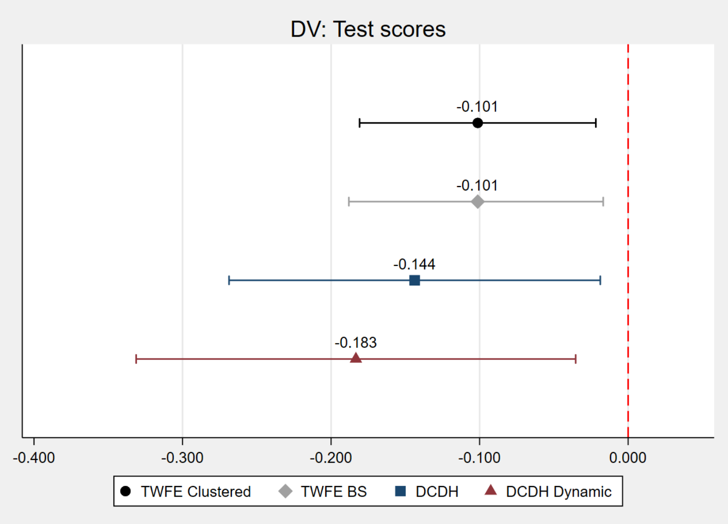
Robustness to heterogenous treatment effects

- From de Chaisemartin and D'Haultfoeuille (2018)



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Robustness to quadratic specification

Table: Exploring non-linearities: Including squared WBDP

	Dependent: Test score (std)		
	All	Dry wards	Rainy wards
WBD potential	-1.133**	-1.423**	-0.346
	(0.557)	(0.645)	(1.785)
WBDP Squared	1.152	1.560	3.272
	(0.974)	(1.072)	(8.976)
Obs.	368,444	178,449	189,995
Clusters	3,842	1,669	2,173

Note: Standard errors in parentheses clustered on ward. WBD Potential is two-week average share of area of ward covered in stagnant water, $\sim$(0,1). Dry ward if mean precipitation $<$ 1000 mm precipitation. Rainy ward if $\geq$ 1000 mm precipitation. Wave, Calendar month, Ward fixed effects, and ward-level 2-week sum of precipitation. Household covariates included are child's gender and age, and mother's age and whether secondary education or above.

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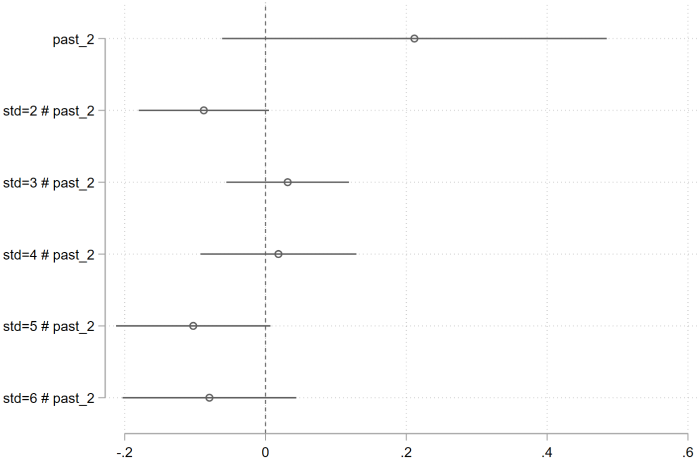
Absence



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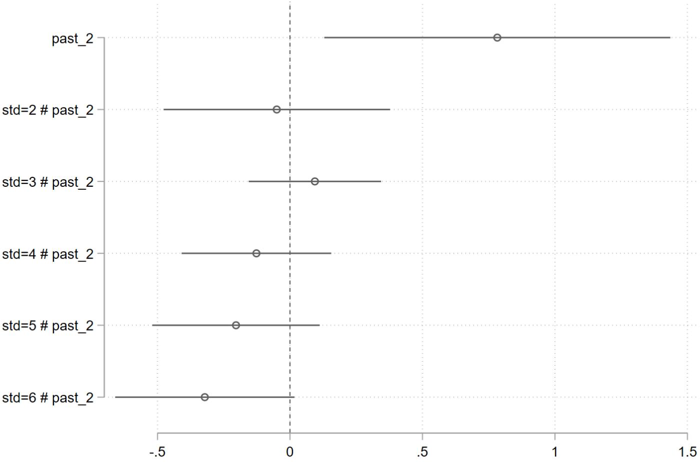
Absence in warm wards (>24 deg C)



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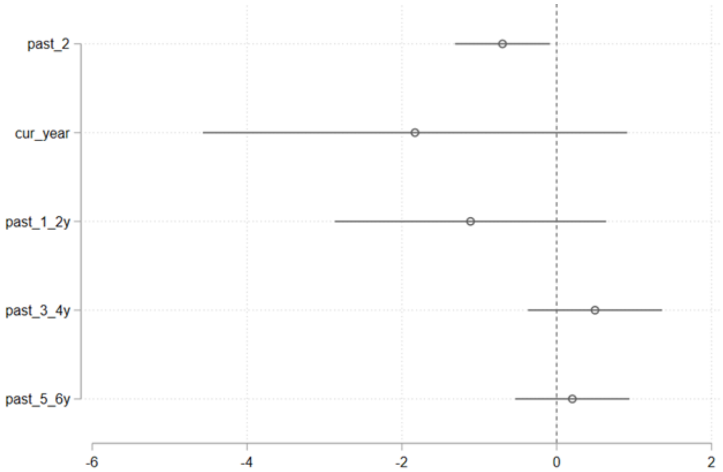
Long-term effects: all



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Validating WBDP: measured stagnant water exposure

	(1)	(2)
	Dependent: Time to water source (minutes)	
	Non-natural (tap, well, spring)	Natural (dam, lake, pond)
WBD Potential	-4.967	-68.38**
	(23.80)	(28.98)
Mean DV	40	49
Obs.	13,546	2,514
Clusters	241	176

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