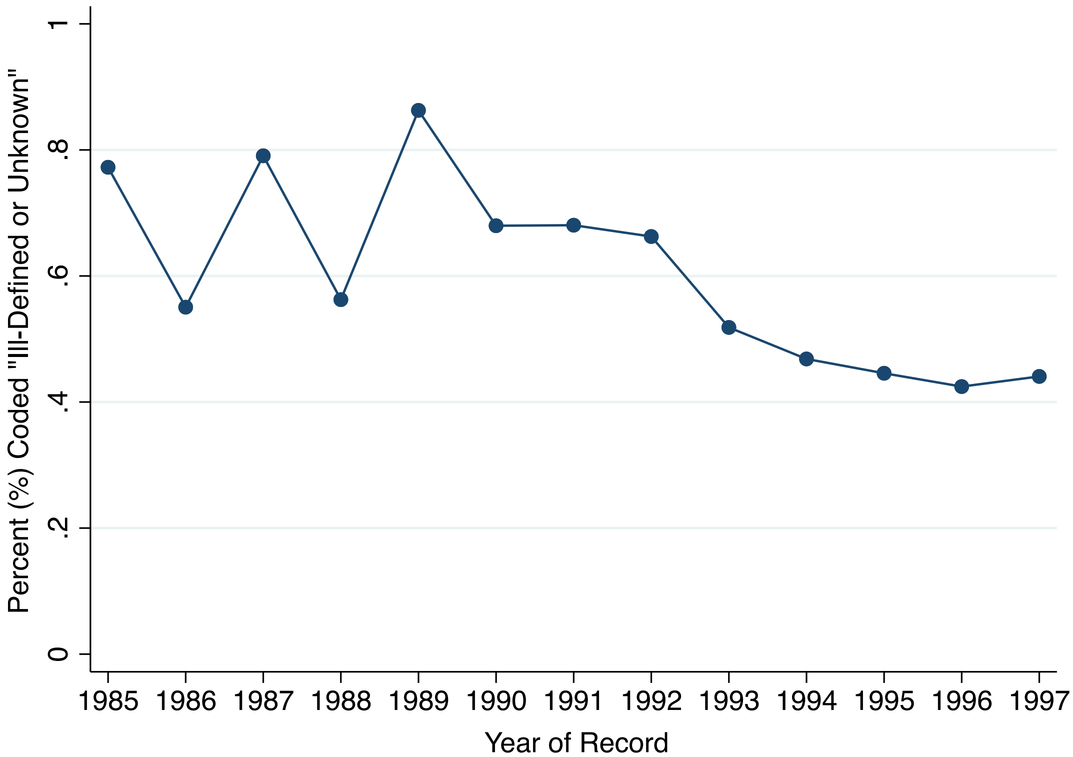
ONLINE APPENDIX

Urban Water Disinfection and Mortality Decline in Lower-Income Countries

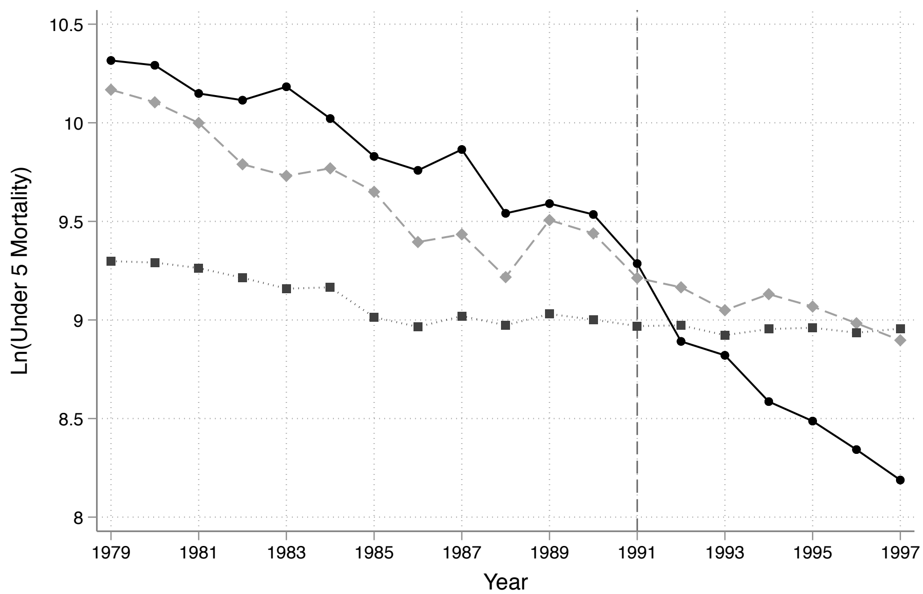
Sonia R. Bhalotra, Alberto Diaz-Cayeros, Grant Miller, Alfonso Miranda, and Atheendar S. Venkataramani[||]

Figure A1 – Quality of Death Registration Records



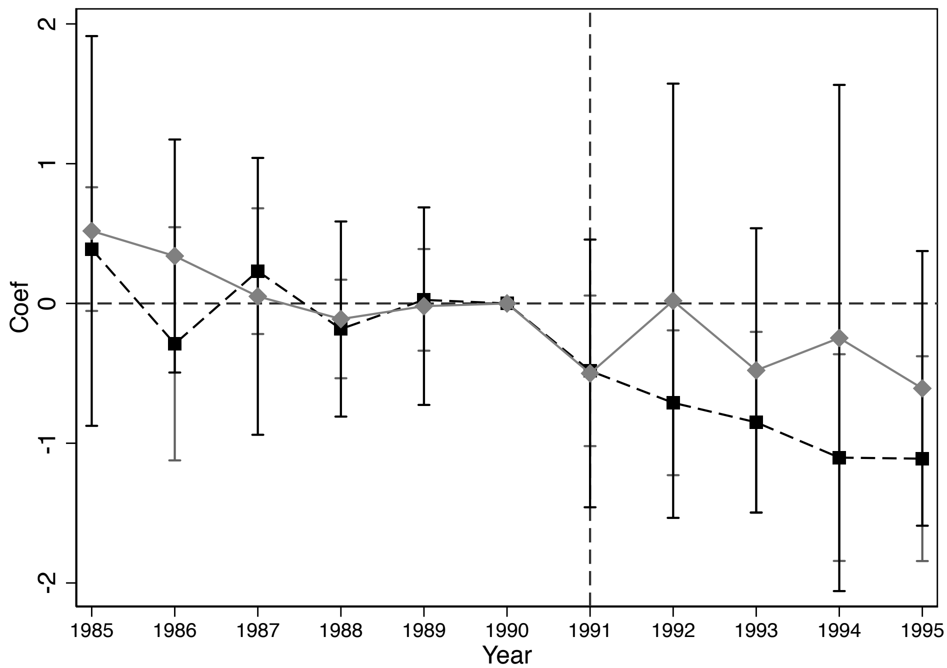
Notes: We conducted two separate analyses to assess the quality of Mexico's vital registration records during our study period. First, we examined the number of death records for which the cause of death was missing or not coded, finding that 0% of death records had missing causes. Second, we assessed the prevalence of causes of death coded as "ill-defined or unknown causes of mortality" over time, which we plot in the above Figure. While the share does decline slightly after 1990, the prevalence of unknown cause codes is less than 1% through the period. We note that these analyses do not address the potential for changes in the completeness of recording deaths from any cause and more accurate attribution and assignment of causes of death over time.

Figure A2 – National Trends in Under-5 Deaths for Control Diseases



Notes: Figure plots national trends logged under 5 deaths from diarrheal diseases (black circles), respiratory control diseases (light grey diamonds), and non-infectious diseases (dark grey squares) for the period 1979-1997 using data from the Mexican Vital Statistics registry. We plot logged number of deaths instead of death rates here because municipality level data on the number of births each year are not available prior to 1985. As noted in the main text, we formally tested for structural breaks for each disease between 1985-1995 (Quandt 1960), remaining agnostic about the exact break point in the time series. Specifically, we calculate the F-statistic on different user-specific break points in the window, with the largest F-statistic across tests of different time points is used to identify the break point. We ran these tests after detrending the time series using the estimated linear time trend over 1979-1985, after which the null hypothesis of a unit root in the time series prior to any structural breaks was rejected by an augmented Dickey-Fuller test (e.g., see Hansen 2001). We found a statistically significant trend break for diarrheal diseases in 1991, which is timed exactly with PAL ($F = 7.82$, $p = 0.013$). We do not find evidence of any trend breaks timed with PAL for either respiratory diseases (break year 1987, $F = 2.76$, $p=0.12$) or non-infectious childhood diseases (break year 1989, $F = 6.92$, $p=0.018$).

Figure A3 – Heterogeneous Treatment Effects by Pipe Breaks (Measured in 2005)



Notes: Panels plot event study estimates of PAL impacts on under-5 diarrheal disease mortality rates from versions of Equation (1) that that include interactions with a direct measure of piped water infrastructure quality, pipe main breaks per kilometer of piped water infrastructure. These data, described in the notes to **Figure 7**, were obtained from the International Benchmarking Network for Water and Sanitation Utilities (IB-NET, http://www.ib-net.org/) and are available for only 16 municipal water systems (compared to 1,429 in our main analyses) and only for the year 2005. Consequently we treat these estimates as suggestive. The figure plots marginal effect estimates for municipalities below (black) and above (grey) the median of the pipe breaks measure. Treatment effect estimates are larger in magnitude where pipe breaks are lower. However, these differences are not statistically significant given the small sample size.

Table A1 – Difference in Difference Estimates Using Quartic Transform of Mortality Rates

Outcome	Diarrheal Diseases	Diarrheal Diseases		Diarrheal Diseases	All Diseases
Control Group	*Respiratory Diseases*	*Non-Infectious Diseases*		*Large Cities*	*Large Cities*
1(Diarrhea)*1(Post)	-0.065	-0.088	1(Small)*1(Post)	-0.056	-0.167
	(0.025)	(0.026)		(0.086)	(0.083)
1(Diarrhea)*1(Post)*Year	-0.045	-0.066	1(Small)*1(Post)*Year	-0.078	-0.067
	(0.009)	(0.009)		(0.022)	(0.045)
N	31,082	31,082	N	15,717	15,717
R-squared	0.44	0.3	R-squared	0.45	0.54

Notes: Models are identical to those presented in *Table 3* of the main text, except here we use the quartic root transform of instead of the inverse hyperbolic sine. Robust standard errors, correcting for clustering at the municipality level, are provided in parenthesis. All models include municipality and year fixed effects. Importantly, the coefficient estimates cannot be interpreted in the same way as a log transform or inverse hyperbolic sine. Given difficulties in getting generalized linear model versions of these regression to converge, we were unable to calculate marginal effects for these coefficients. Nevertheless, we note that the substantive findings remain similar to those presented in the main text.

Table A2 – Difference in Difference Estimates Using Death Counts

Outcome	Diarrheal Diseases	Diarrheal Diseases		Diarrheal Diseases	All Diseases
Control Group	*Respiratory Diseases*	*Non-Infectious Diseases*		*Large Cities*	*Large Cities*
1(Diarrhea)*1(Post)	-0.082	-0.182	1(Small)*1(Post)	-0.010	-0.072
	(0.026)	(0.030)		(0.158)	(0.085)
1(Diarrhea)*1(Post)*Year	-0.119	-0.121	1(Small)*1(Post)*Year	-0.122	-0.036
	(0.010)	(0.014)		(0.059)	(0.038)
N	31,082	31,082	N	15,717	15,717
% Decline by 1995 Due to PAL	*-59%*	*-67%*		*-50%*	*-21.6%*

Notes: This table is identical to *Table 3* in the main text except here we data on death counts between 1985-1995. We use a negative binomial model to model the number of deaths. We use the estimated coefficients to calculate the percent relative decline in diarrheal deaths. These estimated effects are substantively similar except for models examining deaths from all-causes, for which estimates suggest smaller (and statistically insignificant) effects. Robust standard errors, correcting for clustering at the municipality level, in parenthesis.

Table A3 – Statistical Inference After Clustering at Higher Geographic Levels

Outcome	**Diarrheal**	**Diarrheal**		**Diarrheal**	**All**
Control Group	*Respiratory*	*Non-Infectious*		*Large Cities*	*Large Cities*
1(Diarrhea)*1(Post)	***-0.132***	***-0.182***	***1(Small)*1(Post)***	***0.00262***	***0.0543***
P-value, municipality clustering	0.002	0.000	P-value, municipality clustering	0.54	0.046
P-value, state clustering	0.004	0.000	P-value, state clustering	0.53	0.110
P-value, wild cluster bootstrap, state-level	0.002	0.005	P-value, wild cluster bootstrap, state-level	0.67	0.53
1(Diarrhea)*1(Post)*Year	***-0.0857***	***-0.122***	***1(Small)*1(Post)*Year***	***-0.112***	***-0.131***
P-value, municipality clustering	0.000	0.000	P-value, municipality clustering	0.003	0.096
P-value, state clustering	0.004	0.003	P-value, state clustering	0.062	0.21
P-value, wild cluster bootstrap, state-level	0.005	0.000	P-value, wild cluster bootstrap, state-level	0.19	0.53

Notes: Estimates of Equations 3 and 4 of the main text with p-values obtained from clustering at the municipality-level (as in *Table 3* of the main text) and the state-level. For state-level clustering, we additionally implement the wild cluster bootstrap-t method of Cameron, Gelbach, and Miller (*Review of Economics and Statistics* 90(3), 2008). Point estimates are the same as those presented in those presented in *Table 3* of the main text.

Table A4 – Diarrheal Mortality Decline and In-Migration

	(1)	(2)	(3)
ΔDiarrhea	0.00014	0.000192	0.0002
	(0.000048)	(0.000046)	(0.000074)
N	498	498	498
R-squared	0.002	0.133	0.238
BaseDiar	0.00016	0.00021	0.00055
	(0.00068)	(0.00059)	(0.00075)
N	498	498	498
R-squared	0.0001	0.106	0.201
Controls			
Municipality Char	No	Yes	Yes
State FE	No	No	Yes

Notes: To assess potential non-random migration as a function of exposure to PAL, we use data from the public use 1995 Mexican Population Census Microdata, a representative 1.5% sample which allows us to identify individuals who lived in a different municipality 5 years prior to survey (i.e., pre-PAL, which was in 1991). In prior censuses, only interstate migration is identifiable. The identity of the municipality the individual moved from is not known, though the current municipality of residence is recorded. Focus on reproductive age adults (i.e., men and women ages 18-40), we can construct the in-migration rate for each municipality (in our data we can identify nearly 500 municipalities). On average, the share of individuals living in a given municipality who migrated from elsewhere over the preceding 5-year period was 9.3%.

To assess whether in-migration responded to changes in diarrheal disease environment, we estimated models of the following form:

$$Migration_{ij} = \alpha_0 + \alpha_1 (\Delta Diarrhea_j) + X_{(i)(j)} + u_{ijt}$$

$$Migration_{ij} = \alpha_0 + \alpha_1 (BaseDiar_j) + X_{(i)(j)} + u_{ijt}$$

Here, *i* represents the municipality and *j* the state. $Migration_{ij}$ is the proportion of individuals in a given county in 1995 who lived in another county 5 years prior; $\Delta Diarrhea_j$ is the change in under-5 diarrheal disease mortality in the post versus pre-periods (defined so that positive values reflect larger declines); $BaseDiar_j$ is pre-intervention baseline diarrheal mortality rate change; and $X_{(i)(j)}$ represent municipality specific, pre-intervention controls and/or state-fixed effects.

The first regression assesses whether in-migration changed as a function of the degree of decline in diarrheal mortality. We find that areas with larger declines in diarrheal mortality had higher rates of immigration. While the estimates are precise, they are substantively small. The estimates suggest that the average drop in diarrheal mortality pre-post PAL was associated with a small 0.08% point increase in the proportion of in-migrants, which is less than 1/100th of the mean. These small estimates are robust to the inclusion of controls. The second regression leverages the insight that areas with higher pre-intervention diarrheal mortality rates gained more from PAL (see our original working paper, Bhalotra et al (2018) for further details). Here, too, we find small and, this time, imprecisely estimated coefficients. For example, at the mean of baseline diarrheal mortality rate, we would expect only a 0.16% pt increase in in-migration. We conclude that nonrandom migration is unlikely to be driving our findings.

Table A5 – Parametric Estimates of Heterogeneous Effects of PAL by Pre-Program Infrastructure

Model estimates	
1(Diarrhea)*1(Post)	0.026
	(0.106)
1(Diarrhea)*1(Post)*Year	-0.0937
	(0.0377)
Piped Water Covg*1(Diarrhea)*1(Post)	-0.0704
	(0.221)
Piped Water Covg*1(Diarrhea)*1(Post)*Year	-0.0519
	(0.0786)
Sewage Covg*1(Diarrhea)*1(Post)	-0.581
	(0.272)
Sewage Covg*1(Diarrhea)*1(Post)*Year	-0.0398
	(0.0954)
Municipality-Disease-Year Obs (Municipalities)	42,234 (1,280)
R-squared	0.41

Notes: Estimates from a variant of Equation 3 in the main text, where each parametric term is interacted with pre-PAL municipality infrastructure characteristics obtained from a 10% sample of the 1990 census. These estimates complement the non-parametric models examining treatment effect heterogeneity presented in *Table 6* of the main text. Models include both sets of control diseases to improve power (allowing pre-existing trends, PAL program impacts, and heterogeneity in infrastructure characteristics to vary separately for each control disease). Models also include full sets of interactions with pre-PAL municipality average (logged) household income, years of schooling completed, and share of population indigenous, also obtained from the 1990 census. We include the additional control variables in order to better identify the true interaction effect between baseline amenities and disinfection. This is because, in a cross-section, areas with better baseline amenities on average are better off, having better socioeconomic outcomes and exhibiting lower rates of diarrheal disease mortality. Failing to account for socioeconomic characteristics may lead to falsely attenuated estimates of complementarities between infrastructure and disinfection, because the infrastructure may reflect baseline risk: that is, we would expect areas with lower baseline risk – which on average have better piped water and sewage infrastructure – to benefit less from a clean water intervention.

We only report the specific coefficients that capture main program effects ($1(\textit{Diarrhea}) \times 1(\textit{Post})$ for the level break and $1(\textit{Diarrhea}) \times 1(\textit{Post}) \times \textit{Year}$ for the trend break) and coefficients estimating the interactions between main program effects and pre-existing piped water and sewage coverage, respectively. Standard errors, clustered at the municipality level, are provided in parentheses.

Of note, the number of municipalities represented in our sample (n = 1,280) is smaller than the number of municipalities in our main analyses (n = 1,429), owing to the missing information on infrastructure characteristics for smaller municipalities who may not have been represented in a 10% random sample of the 1990 census.