Comment on "Re-Examining the Contribution of Public Health Efforts to the Decline in Urban Mortality"

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Abstract:

We address points raised by Anderson et al. (2020), which commented on our prior work. After correcting unambiguous data mistakes, our revised estimates suggest that municipal water disinfection (filtration) explains 38% of the total mortality rate decline in our sample cities and years – a result not very different from our 43% original estimate. However, effects on infant mortality rates are smaller than in our original analysis. Much of the difference between ACR's analyses and ours is due to the coding of partial intervention years and to differences in population denominators, for which ideal data are difficult to find.

We thank Kim Singer Babiarz for assistance in preparing this comment as well as Mark Anderson, Kerwin Charles, and Daniel Rees along with Seema Jayachandran and anonymous referees for valuable comments and suggestions. A more detailed version of this comment is available at: https://ngmiller.people.stanford.edu/role-public-health-improvements-health-advances-20th-century-united-states.

1. Introduction

In this comment, we address points raised by Mark Anderson, Kerwin Charles, and Daniel Rees's paper entitled "Re-Examining the Contribution of Public Health Efforts to the Decline in Urban Mortality" ("ACR"). ACR is, in part, an examination of our 2005 *Demography* article entitled "The Role of Public Health Improvements in Health Advances: The 20th Century United States" ("CM"). During the summer of 2018, we shared data and code from CM with ACR. They replicated our original results. In conducting new analyses of both milk purification and water/sanitation technologies in American cities in the early 20th century, ACR also identified differences between our original analysis and their new analysis. ACR communicated with us about these issues in a helpful and collegial manner. We very much appreciate their constructive feedback. In light of their results, we have evaluated the issues further. We report our findings here.

The issues raised by ACR generally fall into three categories: (1) transcription errors, (2) assignment of differing clean water intervention dates (including coding of partial intervention years), and (3) the population denominators used in constructing mortality rates. Several of the transcription errors identified in ACR are in fact mistakes in the original paper, which we are grateful to have these identified.[1] Otherwise, a large share of the discrepancy in the estimates between CM and ACR is due to the coding of partial intervention years and to the construction of population denominators for mortality rates when such denominators are not known for certain.

[1] The dataset available online includes updates to correct these errors: https://ngmiller.people.stanford.edu/sites/g/files/sbiybj4811/f/demography2005_0002_final.dta. Throughout this comment, we use the corrected CM total mortality rates and infant mortality rates estimates as the basis for comparison rather than those originally reported in CM (2005).

After carefully considering the points raised by ACR and correcting the unambiguous mistakes in our original data, our revised estimates suggest that municipal water disinfection (filtration) explains 38% of the total mortality decline in our sample cities and study years – a result not dramatically different from the estimated 43% in the original paper. However, effects on infant mortality appear more sensitive to these adjustments. Based on these results and others in the literature, we nonetheless continue to believe that these technologies have been important for historical urban mortality decline.

2. The Findings of Cutler and Miller (2005)

In our earlier paper, we estimated panel data models examining the impact of water filtration and chlorination on mortality. Our primary outcomes were the total mortality rate in the city as well as infant morality rate and mortality rates by cause. Our central result was that 43% of the reduction in total mortality between 1900 and 1936 was a result of clean water interventions.

That original analysis had one computational error, pointed out to us by Alsan and Goldin and discussed further in an unpublished note (Cutler and Miller, 2016): we used the change in log points in the numerator and divided it by the percent change in deaths in the denominator. Correcting this error by using percent changes for both leads to a corrected clean water share of improved mortality of 41%.[2] We use this estimate in examining the effect of the changes proposed by ACR.

3. Summary of Transcription Errors

[2] An erratum note is available online at https://ngmiller.people.stanford.edu/sites/g/files/sbiybj4811/f/erratum.pdf.

ACR identified several data transcription and coding errors made in CM. First, ACR identified a coding error made in calculating lagged mortality rates for the city of Memphis, which did not report any mortality data in the year 1916. Although Memphis is correctly coded as missing for 1916, lagged rates for the 5 subsequent years were erroneously coded as zeros rather than missing.

Second, for years 1910-1917, CM digitized race-specific mortality rates for the 9 sample cities for which the Bureau of the Census reported data disaggregated by race. These race-specific mortality rates were then weighted using the population share in each race category to obtain total mortality rates. Although the rates calculated in this way do not exactly match the overall rates reported directly for total mortality, the two are close.[3] For the purpose of this re-assessment, we re-entered the contemporaneously reported total mortality rates reported for the population as a whole using the annual *Mortality Statistics* volumes for years 1910-1917.

Third, ACR identified several errors in the infant mortality rates used in CM. Some of these are miscellaneous transcription errors (for example, there were 856 infant deaths in Milwaukee in 1926, but the number of infant deaths was erroneously recorded as 865; these errors are reported in detail in ACR Appendix Table 8). However, they do not substantively affect the results. Additionally, ACR identified a systematic error in the CM infant mortality rates for 9 cities in years 1910-1917. As was done for all-cause mortality, CM use age-specific death counts by race for these city-years and then weight race-specific infant mortality using corresponding race-specific population shares. However, these weights were erroneously

[3] For example, in 1914, the *Mortality Statistics* volume reports that the city of Cincinnati had an all-cause mortality rate of 1521.2 per 100,000 among white residents (93.7% of the population) and a mortality rate of 2959.6 per 100,000 among non-whites (6.3% of the population). CM calculated the total mortality rate among all residents as $(1521.2 \times 0.937106) + (2959.6 \times 0.062894) = 1611.667$. Aggregate total mortality rates reported in the same *Mortality Statistics* volume were 1599.0 for Cincinnati in 1914.

applied to infant death counts prior to calculating infant mortality rates, which were not ultimately calculated. Instead, the weighting approach should have been applied after calculating infant mortality rates for these city-years. This is a mistake that we are grateful to have identified.

After correcting these errors, our estimate of the effect of water filtration and chlorination on total mortality rates falls from -0.16 (p-value 0.03) to -0.13 (p-value = 0.03) (Table 1, Columns 1-2), with each estimate falling within the 95% confidence interval of the other. However, for infant mortality rates, the corrected estimate falls meaningfully, from -0.43 (p-value 0.005) to -0.13 (p-value = 0.02) (Table 1, Columns 3-4).[4] Hereafter, we use the corrected total mortality rate and infant mortality rate estimates as the basis for comparison rather than those originally reported in CM (2005).

4. Assignment of Clean Water Intervention Dates

ACR identify a number of differences in clean water intervention dates between their analysis and those used by CM. Reviewing the data more closely, differences in dates generally appear to be the result of two factors: differences in dates reported in various historical sources and differences in coding when an intervention was introduced in a phased manner over multiple years. All told, out of 13 total cities, ACR use water filtration dates for 4 cities and water chlorination dates for 7 cities that are different than the CM dates.[5]

[4] We note that given the composition and major causes of infant mortality during this era (concentrated in the neonatal period), along with the practice of exclusive breastfeeding, it is unclear that one would necessarily expect infants to be the demographic subgroup most sensitive to clean water interventions (Thomasson and Treber, 2004). For example, Knutsson (2018) finds that clean water technology reduced Stockholm's total mortality rates by about 30%, but do not find statistically significant effects on infant mortality. There are also new questions raised about the accuracy of population denominators in US historical vital statistics (see Eriksson et al. (2017)).

[5] When allowing for fractional coding for years in which interventions were partially available, CM and ACR clean water technology variables differ in value for all 13 cities.

On differences in intervention dates used by ACR and CM, different historical sources give different dates for clean water interventions. When writing the original CM paper, we addressed this inconsistency by making phone calls to individual waterworks to verify intervention dates through each waterworks' own records. Reaching some confidence on intervention dates through discussions with waterworks employees, in part, ultimately motivated our choice of dates (and cities) to incorporate. ACR use historical articles providing intervention dates. Table 2, Columns 1 and 2 show the effect of using the alternative dates put forward by ACR on our results. The filtration coefficient falls from -0.13 (p-value = 0.027) in the CM analysis to -0.09 (p-value = 0.036) using ACR intervention dates.[6]

Philadelphia provides an illustrative example of the differences due to coding when an intervention was introduced in a phased manner over multiple years. Philadelphia adopted filtration technology incrementally between 1902 and 1909: filtration systems were installed in Lower Roxborough in 1902, Kittanning in 1905, and Lancaster in 1906. However, the largest facility, Torresdale, which provided the majority of Philadelphia's drinking water (and was the largest facility in the world at the time), was not completed until 1909. ACR use 1906 as the date of filtration, while CM use 1908. Upon reconsideration of Philadelphia's history, we would actually be inclined to think that 1909 is the most appropriate date to use in this case. We do not see a case for 1906 being the best choice of year.[7]

[6] Results obtained using ACR intervention dates throughout this comment differ slightly from those reported in Tables 14 and 15 of an earlier working paper version (see ACR (2020)) because we recode lagged intervention variables to correspond to the ACR intervention dates.

[7] When adjusting Philadelphia's water filtration date to 1909, point estimates for total mortality increase to -0.14 (p-value = 0.027) using CM (2005) dates for all other cities, -0.11 (p-value = 0.032) using ACR (2020) dates for all other cities, and -0.16 (p-value = 0.006) when using ACR (2020) dates recoded as indicators. When adjusting Philadelphia's date to 1909, point estimates for infant mortality are to -0.13 (p-value = 0.05) using CM (2005) dates for all other cities, -0.05 (p-value = 0.475) using ACR (2020) dates for all other cities, and -0.14 (p-value = 0.012) when using ACR (2020) dates recoded as indicators.

Finally, CM code water disinfection and sanitation interventions using indicator variables (taking a value of 1 if an intervention was active at any point during a given year), while ACR use in some instances a partial/fractional intervention coding for a subset of intervention years (in monthly increments, or twelfths).[8] Though seemingly minor, this coding difference matters for the results. Table 2, Column 3 shows that simply recoding partial years of an intervention to full years (but otherwise using ACR dates) increases the ACR filtration estimate from -0.09 (p-value = 0.036) to -0.15 (p-value = 0.010), a value greater in magnitude than our original estimate. In principle, the idea of using partial intervention year coding is a good one. However, the ideal coding should be based on the share of clean water provided to people weighted by how likely they were to die or water-born disease. Without this information, we hesitate to use partial year data.

Ultimately, because some degree of judgment is required, we take an empirical approach to assessing the sensitivity of the CM and ACR results to intervention dates. Specifically, we re-estimate our original specification using all 8,192 possible combinations of CM and ACR intervention dates.[9] We also repeat this exercise changing ACR's coding of fractional intervention years to indicator variables for all cities. Focusing first on total mortality rates, Figure 1, Panel A shows that no combination of dates using either partial intervention year coding or exclusive indicator variable coding produces an estimate outside the confidence interval using our original dates.

[8] The first year of water filtration interventions is coded as partial/fractional years for eight cities. The first year of water chlorination is coded as partial/fractional years for four cities. Finally, three cities have partial/fractional coding for more than one intervention year (two cities with two years each of fractional coding and one city with three years; in two cases, these values decrease over time before taking a value of 1).

[9] When allowing for partial intervention years, CM and ACR intervention variables differ in at least some years for all 13 cities, implying a total of $2^{13} = 8{,}192$ possible unique combinations of city-level intervention variables. When recoding ACR dates to indictors (not allowing for partial years), intervention variables used CM and ACR differ for only 9 cities, leading to a total of $2^{9} = 512$ possible unique combinations of city-level dates.

To further explore sensitivity, we also adopt a 'leave-one-out' strategy, starting with CM dates, ACR dates, and ACR dates recoded as indicators, and we omit one city at a time from the analysis. Figure 2, Panel A shows that the results are generally robust to excluding each city and that no estimates are outside of the confidence intervals of the original CM or ACR estimates (respectively).

Unlike for total mortality rates, estimates for infant mortality rates appear more sensitive to the choice of dates, and in particular, sensitive to the coding of partial intervention years. Table 2, Columns 4-6 show this, using dates and coding choices from both CM and ACR, yielding -0.13 (p-value = 0.03) using CM dates, -0.05 (p-value = 0.45) using ACR dates, and -0.15 (p-value = 0.003) using ACR dates but with partial intervention years recoded as indicators.

Analogous to our sensitivity analysis for total mortality rates, Figure 1, Panel B shows distributions of estimates for infant mortality rates using all possible combination of CM and ACR dates (both as originally coded and recoding ACR partial intervention year variables as indicators). No combination of dates falls outside the confidence interval using our original dates, including when recoding partial intervention years to indicator variables.

Finally, Figure 2, Panel B shows the leave-one-out analysis, leaving each city out of the analysis one at a time using each set of intervention dates. As with total mortality rate estimates, the results are generally robust to excluding each city, and that no estimates are outside of the confidence intervals of full-sample estimates using CM rates or ACR rates (respectively).[10]

5. The Role of Population Denominators

[10] This is true for the revised CM infant mortality rate estimates (after correcting the unambiguous errors described in Section 3), but not for the original CM (2005) infant mortality rate estimates.

Although CM and ACR collect mortality counts and rates from the same sources (US Census Bureau, 1909-1940), ACR identify slight differences in total mortality rates for years 1901-1909 and more substantial differences for years 1910-1917 (there are no differences for years after 1917).[11] After reviewing these differences, they are due to differences in methods for estimating population denominators. CM use mortality rate information as published contemporaneously by the U.S. Bureau of the Census. For years prior to 1917, vital registration systems reported estimated mortality rates, dividing death counts reported by localities by population denominator estimates. Such denominators are only known with near-certainty in population census years. ACR recalculate mortality rates for intervening years using mortality counts and population denominators interpolated between census years.

For total (all-cause) mortality, the U.S. Bureau of the Census reported both mortality counts and mortality rates in its annual *Mortality Statistics* volumes for years 1901-1917 (US Census Bureau, 1909-1940).[12] To calculate mortality rates, the Bureau estimated population in intercensal years using two methods. The 1909 volume of *Mortality Statistics* reported mortality rate estimates for 1901-1909 by assuming that annual population increase was 1/10th of the total increase between 1900 and the preliminary results of the 1910 census. For volumes covering 1910-1917, the Bureau estimated population denominators assuming that the annual population increase was 1/10th of the increase in population between the previous two decennial censuses (1900 and 1910) (US Census Bureau, 1916). After 1917, the Bureau no longer reported mortality rates, but instead reported only death counts. CM uses rates as reported by *Mortality Statistics* for all years for which these rates were published. For all other years (years after 1917), CM

[11] Cause-specific mortality rates do not differ between the two sources.
[12] For infant mortality rates, unlike for total mortality, the Bureau of the Census only reports infant mortality counts in all study years. To calculate infant mortality rates, both CM and ACR transcribe death counts, which are then divided by age-specific infant population projections interpolated between decennial census years.

divides the number of deaths by population estimates interpolated between census year population counts. Alternatively, ACR calculate mortality rates for all years using mortality counts and interpolated population estimates, even when the Bureau of the Census reports rates directly.

While these differences in population denominators seem arcane, they have considerable impact on the results. Table 3 Columns 1-2 show that changing the method of calculating population denominators cuts the estimated effect of water filtration on total mortality rates from -0.13 (p-value 0.03) to -0.08 (p-value 0.014). However, the 95% confidence interval around the CM estimates in Column 1 includes the estimate with different population denominators, and the confidence interval around the estimate with different population denominators in Column 2 includes the CM (2005) estimate as well. Figure 3 considers this issue further, reproducing Figure 1, Panel A using ACR population denominators. Doing so shifts the resulting distributions to the right of those in Figure 1, Panel A.

It is debatable which approach to constructing a time series of total mortality rates is preferable. The approach used by ACR has the appeal of using the same method consistently for all study years. However, it also discards information provided by the Bureau of the Census produced using the Bureau's method of population projection. The approach used by CM uses as much information reported directly by the Bureau of the Census as possible, but as a result uses two different methods for population denominators, before and after 1918. Neither approach incorporates the presumably nonlinear (over time) actual underlying populations due to disruptions such as the 1918 Spanish flu pandemic or World War I – or even due to the clean water interventions themselves.

What would the correct, "gold-standard" approach to constructing population denominators be? Ideally, one would build city-specific life tables to generate intercensal population projections (Wunsch et al., 2002). Building these life tables would require data (or estimates) on four types of population flows: births, deaths, immigration, and emigration. With annual measures of each, the process would be a relatively straightforward population accounting exercise.[13] Annual measures of births and deaths are generally available,[14] but to the best of our knowledge, annual information on immigration and emigration are not. Nonetheless, methods for estimating immigration and emigration may be possible (and cohort sizes in intercensal years could be adjusted accordingly).

6. Conclusion

We are grateful to ACR for the careful re-analysis of our earlier paper and deeply appreciate both the constructive nature of our exchanges with them and the identification of several mistakes in our original paper. Many of the other discrepancies identified, including those that substantively and quantitatively matter most for the results, are ones which we believe require judgment. We have done our best to evaluate these issues, especially the coding of city intervention dates and the construction of population denominators.

Overall, correcting the unambiguous mistakes in our earlier paper yields the finding that municipal water disinfection explains 38% of the total mortality rate decline in our sample cities and study years – a result not materially different from the 43% estimated in the original paper. However, effects on infant mortality rates appear more sensitive to these adjustments and

[13] In cases where birth and death counts were unavailable, one could use age-specific fertility and mortality rates in combination with census year population counts to estimate intercensal populations. Migration data would be required to adjust at-risk population shares in each age category.
[14] Birth counts by city are available for all years beginning in 1915.

markedly smaller than in our original analysis – although we believe the evidence still supports significant, and quantitatively meaningful, effects of clean water on infant mortality as well. Otherwise, a large share of the discrepancy between our analysis and ACR's is, somewhat surprisingly, due to the coding of partial intervention years and to the construction of population denominators for mortality rates. The population is not known for certain, and city populations were changing rapidly in this time period.

More generally, based on the findings of other papers studying municipal water and sanitation interventions in similar historical contexts – some of which were similarly inspired by our paper – we believe that these technologies have been quite important for historical urban mortality decline (Alsan and Goldin, 2018, Anderson et al., 2019, Anderson et al., 2020, Cain and Rotella, 2001, Ferrie and Troesken, 2008, Ketzenbaum and Rosenthal, 2014, Knutsson, 2018, Knutsson, 2020, Ogasawara et al., 2015) and appear to be an important determinant of health in contemporary lower-income cities as well (Ashrof et al., 2017, Bhalotra et al., 2018, Galiani et al., 2005).

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Figure 1: Total and Infant Mortality and Possible Combinations of Intervention Dates

Panel A: Total Mortality Rates, CM (Corrected) Panel B: Infant Mortality Rate, Corrected

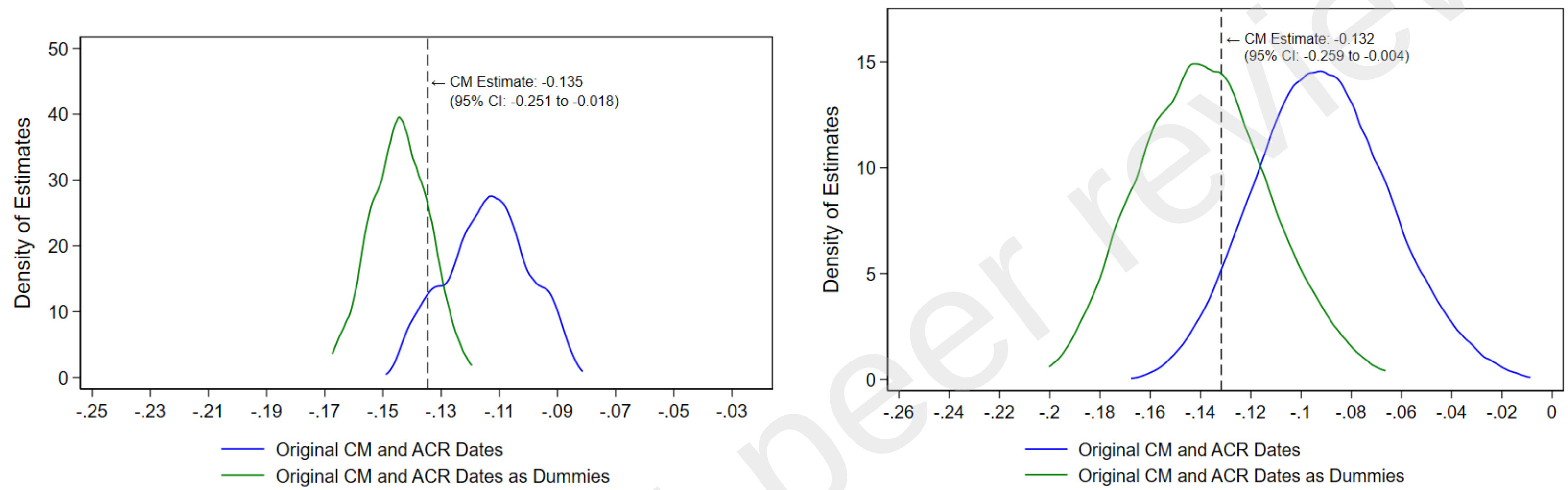
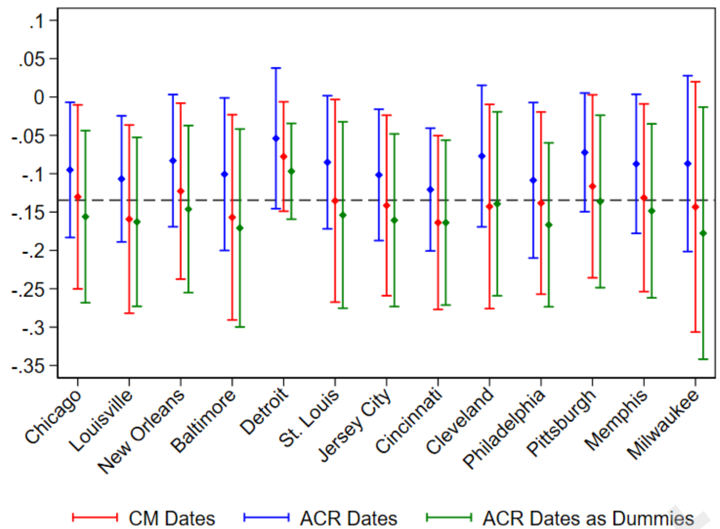


Figure 1 assesses the sensitivity of the CM (2005) total mortality rate and infant mortality rate results to alternative intervention dates. Total mortality rates are contemporaneously reported, as described in Cutler and Miller (2005), with data entry errors corrected. Infant mortality rates used are corrected as described in Anderson, Charles, and Rees (2020). We re-estimate Equation (1) using all possible unique pair-wise combinations of city-level intervention dates used in CM (2005) and ACR (2020). When allowing for fractional year intervention coding, CM and ACR intervention variables differ in at least some years for all 13 cities, implying a total of $2^{13} = 8{,}192$ possible unique pair-wise combinations of city-level intervention variables. When recoding ACR dates to indictors (not allowing for partial years), intervention variables used CM and ACR differ for only 9 cities, leading to a total of $2^9 = 512$ possible unique combinations of city-level dates. Panel A shows the results of this analysis for the total mortality rate (using the corrected CM (2005) approach to population denominators); dashed line indicates point estimates and 95% confidence intervals produced using CM intervention dates. Panel B shows the results for infant mortality rate using ACR (2020) rates which correct data errors in CM (2005); dashed line shows the point estimates and 95% confidence intervals produced using CM intervention dates. Figures show the distribution of each set of resulting point estimates. All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age).

Figure 2: Leave-One-Out Analysis

Panel A: Total Mortality Rates, CM (Corrected)



Panel B: Infant Mortality Rate, Corrected

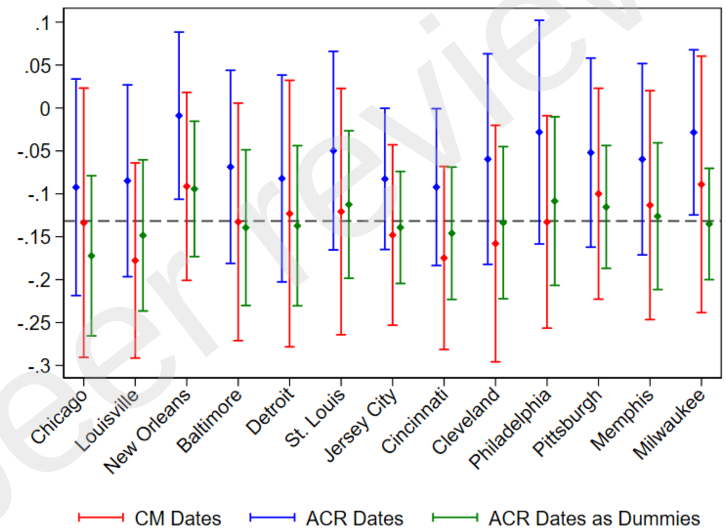


Figure 2 assesses the sensitivity of the CM (2005) results for total mortality rate and infant mortality rate results to alternative intervention dates for each city using a 'leave-one-out' approach. Using corrected CM (2005) total mortality rates (Panel A) and corrected infant mortality rates as reported in ACR (2020) (Panel B), we estimate Equation 1 starting with each alternative set of intervention dates (CM dates, ACR dates, and ACR dates recoded as indicators), and omitting one city at a time from the analysis. Panels A and B show the resulting point estimates and corresponding 95% confidence intervals. All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age). Standard errors are clustered at the city level.

Figure 3: Distribution of Coefficients Using ACR Mortality Rates and All Possible Combinations of Intervention Dates

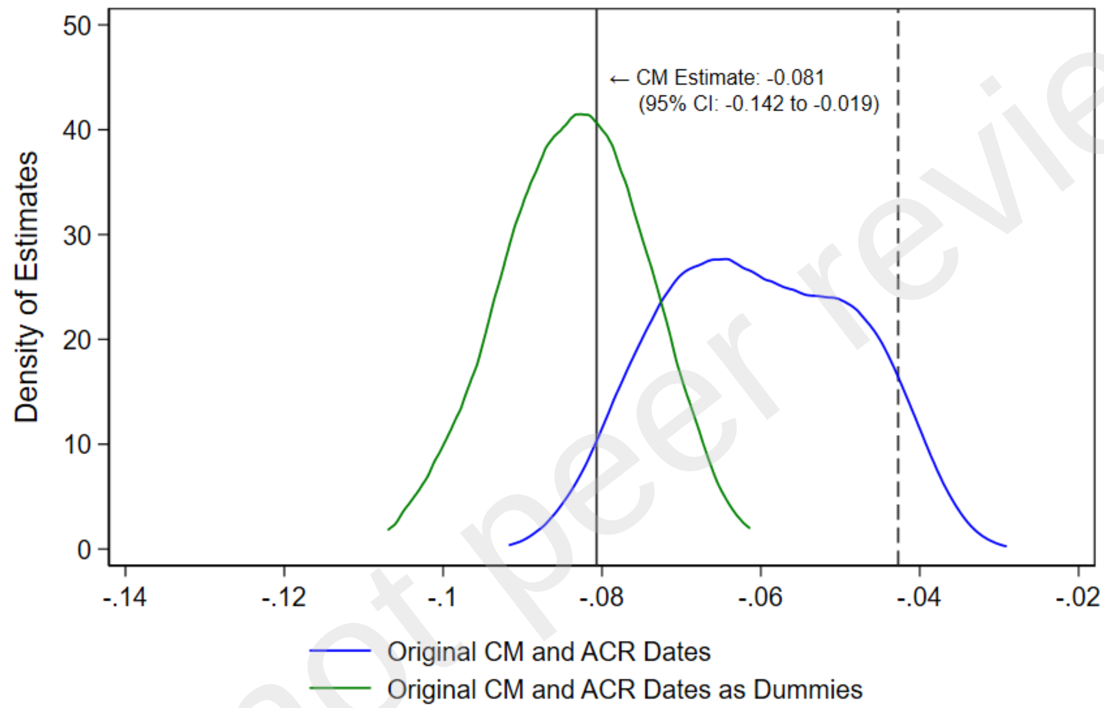


Figure 3 assesses the sensitivity of ACR (2020) total mortality rate results to alternative intervention dates. We re-estimate Equation (1) using all possible unique pair-wise combinations of city-level intervention dates used in CM (2005) and ACR (2020). When allowing for fractional year intervention coding, CM and ACR intervention variables differ in at least some years for all 13 cities, implying a total of $2^{13} = 8{,}192$ possible unique pair-wise combinations of city-level intervention variables. When recoding ACR dates to indictors (not allowing for partial years), intervention variables used CM and ACR differ for only 9 cities, leading to a total of $2^{9} = 512$ possible unique combinations of city-level dates. Figures show the distribution of each set of resulting point estimates. All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age). Solid vertical line shows results using ACR mortality rates and CM intervention dates, and dashed line shows results using ACR mortality rates and ACR intervention dates.

Table 1: Total and Infant Mortality Rate Estimates with and without Transcription Error Corrections

Outcome:	Total Mortality Rate		Infant Mortality Rate	
Mortality Rate Source:	Original	Corrected	Original	Corrected
	(1)	(2)	(4)	(5)
Filtration	-0.16**	-0.13**	-0.43***	-0.13**
	(0.064)	(0.053)	(0.138)	(0.059)
Chlorination	-0.02	-0.01	-0.08	0.02
	(0.034)	(0.024)	(0.104)	(0.043)
Filtration * Chlorination	0.05	0.03	0.06	0.07
	(0.031)	(0.026)	(0.083)	(0.048)
Filtration Within 5 Years	-0.09	-0.07	-0.18*	-0.03
	(0.066)	(0.048)	(0.090)	(0.028)
Chlorination Within 5 Years	0.02	0.01	-0.05	0.03
	(0.022)	(0.014)	(0.101)	(0.028)
Observations	415	410	415	410
R-squared	0.957	0.963	0.828	0.977
F-test	3.085	2.883	5.433	2.827
Prob > F	0.0681	0.0798	0.0136	0.0835

Table shows the results of Equation 1 as presented in Cutler and Miller (2005) and after correcting data transcription and coding errors. Columns 1 and 2 show results for total mortality rate and Columns 3 and 4 show the results for infant mortality rates. Intervention dates are as originally specified in CM (2005). All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age). Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.10.

Table 2: Sensitivity of Total and Infant Mortality Rate Estimates to Alternative Intervention Dates

Mortality Rate Source	Total Mortality Rate, CM (Corrected)			Infant Mortality Rate, Corrected		
Intervention Date Source:	CM	ACR Fractional Coding	ACR as Indicators	CM	ACR Fractional Coding	ACR as Indicators
	(1)	(2)	(3)	(4)	(5)	(6)
Filtration	-0.13**	-0.09**	-0.15***	-0.13**	-0.05	-0.15***
	(0.053)	(0.040)	(0.050)	(0.059)	(0.055)	(0.039)
Chlorination	-0.01	-0.02	-0.01	0.02	0.03	-0.03
	(0.024)	(0.025)	(0.026)	(0.043)	(0.039)	(0.039)
Filtration * Chlorination	0.03	0.03	0.02	0.07	-0.00	-0.01
	(0.026)	(0.027)	(0.025)	(0.048)	(0.043)	(0.041)
Filtration Within 5 Years	-0.07	-0.04	-0.08*	-0.03	0.01	-0.04
	(0.048)	(0.032)	(0.043)	(0.028)	(0.026)	(0.023)
Chlorination Within 5 Years	0.01	-0.01	-0.01	0.03	-0.05*	-0.07*
	(0.014)	(0.014)	(0.018)	(0.028)	(0.028)	(0.034)
Observations	410	410	410	410	410	410
R-squared	0.963	0.962	0.964	0.977	0.978	0.978
F-test	2.883	1.965	3.151	2.827	0.589	6.457
Prob > F	0.0798	0.173	0.0647	0.0835	0.634	0.00753

Table shows sensitivity to the use of alternative water filtration dates in Equation 1 for total mortality and infant mortality rates. Total mortality rates are contemporaneously reported, as described in Cutler and Miller (2005), with data entry errors corrected. Infant mortality rates used are corrected as described in Anderson, Charles, and Rees (2020). Columns 1-3 show results for total mortality, with Column 1 showing results using intervention dates described in CM (2005), Column 2 fixing all dates at those shown in ACR (2020), and Column 3 shows results using dates in ACR (2020) recoded as indicator variables. Columns 4-6 show results for infant mortality rates with Column 4 showing results fixing all intervention dates to those described in CM (2005), Column 5 showing results fixing all dates to those proposed in ACR (2020) as originally coded, and Column 6 shows results fixing all intervention dates to those proposed in ACR (2020), recoded as indicators. All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age). Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Sensitivity of Total Mortality Rate Estimates to Choice of Population Denominator

All Cause Mortality Rate Source:	CM (Corrected)	ACR
Intervention Date Source:	CM	CM
	(1)	(2)
Filtration	-0.13**	-0.08**
	(0.053)	(0.028)
Chlorination	-0.01	-0.04
	(0.024)	(0.026)
Filtration * Chlorination	0.03	0.05**
	(0.026)	(0.024)
Filtration Within 5 Years	-0.07	-0.02
	(0.048)	(0.013)
Chlorination Within 5 Years	0.01	0.02
	(0.014)	(0.011)
Observations	410	410
R-squared	0.963	0.970
F-test	2.883	2.843
Prob > F	0.0798	0.0824

Table shows the results of alternate approaches to population denominators used to calculate total mortality rates, fixing intervention dates at those used in Cutler and Miller (2005). Column 1 shows results using contemporaneously reported mortality rates from CM, with data entry errors corrected, and Column 2 shows results using total mortality rates proposed in ACR (2020). All specifications include sewage treatment dummy variables, lagged mortality, year and city dummy variables, city trends, and demographic characteristics (population share by gender, race, birthplace, and age). Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.10.