What's in the Water? Long-Run Effects of Fluoridation on Health and Economic Self-Sufficiency

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Community water fluoridation has been named one of the 10 greatest public health achievements of the 20th century for its role in improving dental health. I leverage county level variation in the timing of fluoride adoption, combined with restricted U.S. Census data that link over 29 million individuals to their county of birth, to estimate the causal effects of childhood fluoride exposure. Children exposed to community water fluoridation from age zero to five are worse off as adults on indices of economic self-sufficiency (-1.9% of a SD) and physical ability and health (-1.2% of a SD). They are also significantly less likely to graduate high school or serve in the military and more likely to be incarcerated as adults. These findings overturn existing conclusions about safe levels of fluoride exposure and its impact on adult labor market outcomes.

1 Introduction

Over 70% of publicly supplied drinking water in the United States is fluoridated and the CDC has named community water fluoridation as one of the 10 greatest public health achievements of the 20th century (Gooch, 2020). Despite strong evidence that exposure to low levels of fluoride are an effective way to strengthen teeth, many individuals, communities, and industrialized countries oppose water fluoridation out of concern for potential negative health risks. While existing research has not shown conclusive evidence of negative health effects from low levels of fluoride exposure, concerns about the safety of fluoride are supported by a body of research that concludes that early childhood exposure to high doses of fluoride can cause a wide variety of health problems including weakened bones and joints as well as cognitive impairment.[1] The lowest safe level of fluoride exposure is unclear. In this paper, I investigate the impact of early childhood exposure to community water fluoridation on long-run health and labor market outcomes.

The impact of fluoride on health varies based on both the amount and timing of fluoride exposure. This is true for both the positive impacts on dental health as well as the potential negative side effects on teeth, bones, and cognitive function. While it is well established that fluoride exposure makes teeth more resistant to decay, recent controversy has focused on the role of fluoride as a neurotoxin. The meta-study Choi, Zhang and Grandjean (2012) concludes that early exposure to high fluoride levels results in decreased cognitive functions equivalent to nearly one half of a standard deviation in IQ scores. While the majority of reviewed studies focus on subjects with fluoride levels well above recommended levels, some find negative cognitive effects at relative low levels as well. In a follow up meta-study incorporating more recent evidence, Grandjean (2019) concluded that the levels currently recommended for water fluoridation likely exceed safe exposure levels.

While effects on cognitive function might result in negative long-run impacts, recent

[1]See DHHS (2015), Choi, Zhang and Grandjean (2012), and Grandjean (2019) for reviews of this literature.

work has suggested that improvements in dental health play a more prominent role. Glied and Neidell (2010) provides the best evidence in the U.S. context, leveraging variation in the timing of community water fluoridation programs to estimate long run wage effects in the National Longitudinal Survey of Youth – 1979 (NLSY79). Due to the narrow group of birth cohorts in their sample (1957-1964), they are unable to make within-county comparisons; instead, their results rely on the assumption that unobservable county characteristics that affect labor market outcomes are uncorrelated with fluoridation status. They find positive but insignificant wage effects in the full sample—driven by a statistically significant 4% increase in wages among women.[2,3] A more recent paper leverages natural variation in fluoride levels between water treatment plants in Sweden and finds positive effects of fluoride on labor force participation and income (Aggeborn and Öhman, 2017). The authors also estimate effects on cognitive ability and health, finding no effect on either. Their findings rest on the assumption that variation in the geological characteristics, and associated fluoride levels, of local water sources are exogenous to cognitive ability and labor market outcomes. While the Swedish data provide significant precision and measurement advantages over the NSLY79, fluoride exposure is relatively low; over 90% of Swedish observations were exposed to fluoride levels less than those typically added in the United States (0.8-1.2 mg/L). The impact of fluoridating water to these higher levels is unclear.

In this paper, I provide the first large sample and quasi-experimental evidence of the long run health and labor market effects of adding fluoride to the water at these levels. This data includes both respondents to the long form 2000 decennial census as well as American Community Survey respondents from 2001 to 2016 and allows for vast increases in precision, requires much weaker identifying assumptions via inclusion of birth county of fixed effects, and include a broad set of outcomes, birth cohorts, and communities relative to previous

[2]Of course, the small sample sizes afforded by the NLSY (roughly 12,000 individuals) result in relatively wide confidence intervals. They cannot reject effects on earnings as small as -0.6% or as large as 5% in the full sample. Similarly, they cannot reject effects as small as 0.6% or as large as 8% for women.

[3]I also conduct a replication exercise and find that the model of Glied and Neidell (2010) estimates negative wage effects from fluoride in my sample. These results are discussed in Section 5.3.

work.[4] I use a stacked difference-in-differences strategy that compares outcomes of county-birth-cohorts with exposure to fluoridated water to those without any, while controlling for county and year of birth. This stacked design is unbiased even in the presence of heterogenous treatment effects (Cengiz et al., 2019).[5]

I find that consumption of fluoridated water from age zero to five results in a 1.9 percent of a standard deviation decrease in adult economic self-sufficiency, 1.2 percent of a standard deviation decrease in physical ability and health, a 0.4 percentage point increase in likelihood of being incarcerated, a 1.0 percentage point decrease in military service and a 1.5 percentage point decrease in high school graduation.[6] To put some of these results in context, I compare them to Bailey et al. (2020) who estimated the beneficial effects of early childhood access to food stamps using a similar set of outcomes. Taking point estimates from both studies at face value, this suggests that early childhood fluoride exposure has the potential to erase approximately two-thirds of the self-sufficiency benefits and four-fifths of the decreases in incarceration caused by early childhood utilization of food stamps.

The net effect of fluoride is negative; even at levels previously thought to be safe, the tooth strengthening effect of fluoride provides less benefit than fluoride's corresponding negative impact on other determinants of health and economic self-sufficiency. While it is difficult to disentangle all the mechanisms at play, the observed decrease in high school graduation rates is consistent with negative cognitive effects.[7] While Aggeborn and Öhman (2017) find that fluoride improves labor market outcomes with no evidence of negative cognitive effects, the lower average fluoride exposure in their sample may reduce negative health effects enough

[4]As is shown in Appendix C of Anders, Barr and Smith (2019), this type of large sample administrative data reduces the likelihood that statistically significant results are false positives, improves precision, and reduces publication bias.

[5]This details of this project including the research question, data, outcomes, and empirical approach were pre-specified in Roberts (2021).

[6]These are the estimated effects of treatment on the treated, found by taking the intent to treat effects from Tables 2 and 3 and dividing by 0.37, the population weighted average fraction of a county with initial access to fluoridated water.

[7]Any negative health effect has the potential to impact high school graduation through increased absences or reduced ability to focus. Decreases in cognitive function are still the most likely culprit given evidence of fluoride's effect on IQ scores reviewed in Grandjean (2019) and the direct impact that IQ has academic performance.

to result in a net positive labor market impact driven by improvements in dental health.

A gradual re-evaluation of water fluoridation policies is already underway. In 2015 the U.S. Public Health Service slightly reduced recommended fluoride levels to 0.7mg/L and acknowledged the need for more research into the risks of low-level fluoride exposure (DHHS, 2015). In 2019, the American Dental Association issued a statement that reaffirmed their support of water fluoridation while also welcoming additional research into the potential negative cognitive effects (ADA, 2019). Despite the acknowledged need for more research, fluoride is still being added to a majority of public water supplies in the U.S. and regulations for regions with naturally high levels of fluoride allow water to carry up to 4.0 mg/L, nearly six times the recommended water fluoridation level. The results of this study demonstrate the need to accelerate our re-evaluation of water fluoridation policies. The observed negative impacts of fluoride combined with widespread access to the enamel strengthening benefits of fluoride through toothpaste and dental treatments provides a strong argument for ending the practice of water fluoridation and lowering the maximum levels of fluoride allowed by safe drinking water standards. If water fluoridation practices continue, more research is needed to determine the optimal level of fluoride such that the marginal benefits to dental health are not overwhelmed by negative health costs.

2 History of Fluoride

In the 1930's two dentists, Dr. Frederick McKay and Dr. G.V. Black, discovered that exposure to fluoride in drinking water caused a visible discoloration of teeth while simultaneously protecting teeth against decay. Additional study revealed that impacts on dental health occur during the early stages of tooth development, which begins in utero and is entirely complete by age eight. This childhood exposure directly affects the tooth structure making it more resistant to decay. Cases of tooth decay decrease as water fluoride levels increase but the marginal benefits shrink above 0.7 mg/L and plateau by 1.2 mg/L (Heller, Eklund and Burt, 1997). The most common negative side effect of fluoride is mild dental fluorosis, a cosmetic defect that is characterized by lacy white markings on teeth but does not negatively impact dental health (DHHS, 2015). Dental fluorosis increases in frequency and severity with exposure level. Severe fluorosis is not only cosmetic but includes pitting and damage to tooth structure in addition to visible discoloration. Risk of severe fluorosis increases significantly at fluoride levels above 2.0 mg/L.[8]

Targeting the potential benefits of low-level fluoride exposure, Grand Rapids Michigan became the first city to artificially add fluoride to their public water supply in 1945. Over time other communities followed their example and water fluoridation became a common, although far from universal, practice across the United States. Despite its low financial cost (as low as $0.11 yearly per capita in large cities) and its prevalence, water fluoridation decisions have been rife with controversy since the beginning of the practice (**?**). Referendums regarding water fluoridation typically face strong opposition and frequently fail, with much of the increase in water fluoridation over time being driven by administrative decisions rather than public votes (Sapolsky, 1968). Although specific complaints have changed over time, the opposition to water fluoridation has been based on legitimate concerns as well as conspiracy theories. For example, the concern that human error could lead to toxic levels of fluoride being added to public water supplies was validated by a tragic 1992 accident where nearly 300 Alaskans were poisoned, and one died, after excessively high levels of fluoride were added to a community well. On the other hand, the no-longer-popular conspiracy theory that water fluoridation was part of an elaborate communist plot to poison or control America was shared broadly among anti-fluoridation campaigns in the 1950's (Johnston, 2004).

Although controversy over community water fluoridation has persisted until today, research into the effects of fluoride has also progressed. While early research found that fluoride exposure was most beneficial for children, additional studies have shown moderate benefits for adults as well (DHHS, 2015).[9] Researchers have also explored the effects of fluoride be-

[8] Cases of mild fluorosis affect about 23% of people in the U.S. while severe effect less than 1% (Beltrán-Aguilar, Barker and Dye, 2010)

[9] Adult fluoride exposure reduces the production of tooth-damaging acid by mouth bacteria and simultaneously fortifies teeth making them more resistant to acid. Some evidence suggests that the benefits of adult exposure are concentrated among individuals who were also exposed to water fluoridation during childhood (Singh, Spencer and Armfield, 2003).

yond its impacts on dental health. Fluoride exposure at levels above 4.0 mg/L can cause skeletal fluorosis, resulting in increased joint pain and weakened bones and joints with higher risk of fracture (DHHS, 2015). While additional research has explored potential negative impacts of fluoride on thyroid health or the roll of fluoride as a carcinogen, the majority of research has found no effect of fluoride on those margins (DHHS, 2015).

Increasingly, the focus of research into the health effects of fluoride has been concentrated on the potential for fluoride to act a neurotoxin and negatively impact cognitive functions. Early work using high doses of fluoride in rats showed that fluoride both passes through the blood brain barrier and results in behavioral changes, but whether or not these effects would translate to humans exposed to low doses over a long period of time remained unclear (Mullenix et al., 1995).

The metastudy Choi, Zhang and Grandjean (2012) used evidence from a collection of studies in China and Iran and concluded that high levels of fluoride exposure results in decreases of IQ by nearly half of a standard deviation. While many of the studies included in that review had methodological issues and small sample sizes, additional research by Bashash et al. (2017) in Mexico and Green et al. (2019) in Canada found that in-utero exposure to fluoridated drinking water corresponded to meaningful decreases in IQ scores of young children, especially for boys.[10] These studies accounted for individual level fluoride exposure by measuring fluoride levels in urine of expectant mothers. In fact, a fairly large body of recent literature, many of which are reviewed in the follow-up meta study Grandjean (2019), has, with only a few exceptions, consistently found that fluoride has negative cognitive effects.

Economists have also recently begun studying the labor market effects of fluoride, which are potentially affected by improved dental health or by any negative health effects—cognitive effects in particular. This research was led by Glied and Neidell (2010) who provide the best existing evidence in the U.S. context by leveraging variation in the timing of community water fluoridation programs to estimate the impact of childhood fluoride exposure on adult

[10]A 1.0 mg/L increase in urine fluoride levels corresponded to a decrease of 5.0 and 3.7 IQ points in the two studies respectively.

wages. Unfortunately, the narrow group of birth cohorts in the National Longitudinal Survey of Youth – 1979 (NLSY79), which includes individuals born from 1957-1964, does not provide sufficient variation for within county comparisons or a difference-in-differences analysis. Their results instead rely on the assumption that unobservable county characteristics affecting labor market outcomes are uncorrelated with fluoridation status. Perhaps due to the small sample size and limited identifying variation available among the NLSY79 cohorts, they find positive but insignificant effects in the full sample. The positive effects are driven by a statistically significant 4% increase in wages among women, which the authors interpret as evidence of appearance-based discrimination. The income point estimate for males is zero.

In contrast, Aggeborn and Öhman (2017) leverage natural variation in fluoride levels in Sweden and finds positive effects on labor force participation and income, with larger effects for men. Interestingly, Aggeborn and Öhman (2017) are also able to test for any impacts on cognitive ability or health and find no effect on either outcome. While the Swedish data provide significant precision and measurement advantages over the NSLY79, fluoride exposure is low; over 90% of Swedish observations were exposed to fluoride levels less than those typically added in the United States (0.8-1.2 mg/L).

Water fluoridation remains an important public health topic due it its role as a low-cost way to improve dental health as well as its potential health risks. Despite improving trends in dental health in the U.S. which are frequently accredited to water fluoridation programs,[11] tooth decay is still one of the most common chronic childhood diseases and one in four children below the poverty line have untreated tooth decay (Newacheck et al., 2000; Dye, Li and Thornton-Evans, 2012).

3 Data

The primary data source is restricted individual-level U.S. Census and American Community Survey (ACS) data linked to the Numident file (U.S. birth and death records), made

[11] The prevalence of any tooth decay in adult teeth among adolescents decreased from 90% in the 1960's to 60% by 2004 and the CDC named community water fluoridation as one of the 10 greatest public health achievements of the 20th century (DHHS, 2015).

available through the Census Research Data Centers. This includes ACS years 2001-2016. The Numident file contains each individual's date and location of birth as well as date of death for those who are deceased. Water fluoridation data comes from the 1992 Fluoride Census (a public record provided by the CDC).[12,13,14] Using data from the 1992 Fluoride Census, Figure 12 shows the rollout of community water fluoridation programs by county over time. My analysis sample is limited to individuals born in a U.S. county that was included in the 1992 fluoridation census and successfully linked to its county FIPS code. For computational ease, I collapse the data to the birth-year by birth-county by survey-year level separated by both gender and race. Each collapsed cell is weighted by the number of observations in that cell for all specifications.

Summary statistics are shown in Table 1 for the full sample, by gender, and by treatment status. These summary statistics include basic demographic variables, components of each outcome index (which are explained in detail in the next section), as well as secondary outcomes. While there are minor differences between treated and untreated counties these differences do not affect the internal validity of the stacked difference-in-differences design (explained in Section 4). Sample size is presented as the number of unique individuals, the number of collapsed cells, and the number of observations included in the final sample—which is a function of the stacked differences-in-differences procedure described in Section 4 which includes many duplicated observations.

Defining Fluoride Exposure: Despite access to administrative records, these data sources are still unable to directly identify the amount of fluoride that individuals consumed during childhood. I define treatment at the county-birth-cohort level as the fraction of childhood

[12] Matthew Neidell and Sherry Glied have also generously shared the cleaned version of the 1992 Fluoride Census used in Glied and Neidell (2010).

[13] Via a Freedom of Information Act request to the CDC, I have obtained current natural fluoride levels for each community water system. While these are not used in the current analysis, they do show that counties with lower levels of natural fluoride in their water supply were more likely to add fluoride and, among counties that added fluoride, counties with low natural fluoride levels tended to add fluoride in earlier years.

[14] The locations from both the Numident file and fluoridation records are recorded as strings at the city or county level. These locations are matched to their county level FIPS codes.

years with any potential exposure to community water fluoridation. Childhood here is defined to include the year of an individual's birth through the year that each cohort reaches age five.[15,16] By this definition, a fully treated county-birth-cohort would have lived in a county with a fluoridated water supply from birth. Because counties may have multiple public water systems with different water fluoridation policies and because some households source drinking water from private wells not all individuals in a treated county will drink fluoridated water. I am unable to identify individual children's water fluoridation exposure within a treated county. As a result, this primary treatment definition fails to account for variation in the fraction of each county drinking fluoridated water and the resulting estimates can be interpreted as intent to treat (ITT) effects.[17] Event studies exploring the potential for non-linear treatment affects by age at first exposure are described in Sections 4 and 5.

Outcome Variables: The purpose of this research is to identify the net labor market and health effects of community water fluoridation. Using a construction similar to Bailey et al. (2020), I examine two indices that best capture these outcomes in the ACS: (i) economic self-sufficiency, and (ii) physical ability and health. These indices average across standardized component variables, reversing signs when necessary, such that a more positive value implies a better outcome. The Economic Self-Sufficiency Index includes variables indicating whether or not an individual was in the labor force, worked last year, weeks worked last year, usual hours worked per week, labor income, other income not from public sources, income-to-poverty ratio, not in poverty, reverse coded income from welfare, and reverse coded income

[15]This treatment definition is consistent with other early childhood interventions where years of exposure is the most relevant parameter. Specifically, both Hoynes et al. (2016) and Barr and Smith (2021) use the fraction of early childhood with access to food stamps in order to estimate long run effects in a difference-in-differences setting.

[16]This definition intentionally does not account for differences in fluoridation levels (parts per million). Fluoride levels were determined at the local level, but CDC guidelines adjusted recommended rates relative to average local temperatures which may affect rates of water evaporation and consumption. Because of this, variation in fluoride level between 0.8-1.2 should not reflect actual increases in individual fluoride intake but simply a difference in the amount of water fluoride necessary to reach an equivalent per-person level of fluoride exposure.

[17]Section 5 discusses the implied treatment on the treated (TOT) effects and presents results from an alternative treatment definition that directly incorporates the percent of a county exposed to water fluoridation.

from supplemental security.[18] The Physical Ability and Health Index includes reverse coded information on the presence of an ambulatory or independent living difficulty, a cognitive difficulty, a vision or hearing difficulty, and a self-care difficulty.[19]

The index approach alleviates concerns about multiple hypothesis testing and improves statistical power (Kling, Liebman and Katz, 2007). In addition to these two primary outcomes, I also estimate effects on the secondary outcomes of high school graduation, military service, survival to 2020, and incarceration. The next section outlines the details of my analytical approach.

4 Analytical Approach

I use a stacked difference-in-differences strategy leveraging the staggered adoption of community water fluoridation across the United States. This design compares outcomes of county-birth-cohorts with exposure to fluoridated water to those without any, while controlling for county and year of birth. This strategy does not rely on the exogeneity of fluoride levels conditional on observables, but on the weaker assumption that the shift in health and labor market outcomes of untreated individuals across time effectively proxies for the shift in outcomes that would have occurred for individuals drinking fluoridated water in the absence of fluoride treatment. While I am using a stacked differences-in-differences design, the basic non-stacked version is a useful starting point to discuss merits of this approach. That non-stacked reduced form difference-in-differences specification would be:

$$Y_{ct} = \theta_c + \delta_{s(c)t} + \mu X_{ct} + \beta(Exp6)_{ct} + \epsilon_{ct} \tag{1}$$

In this specification, $(Exp6)_{ct}$ represents a county-birth cohort's cumulative exposure to fluoridated water during childhood (age 0-5). The long run health and labor market

[18] Dollar values are inflation adjusted to 2016 dollars prior to index creation.

[19] While the variables "ambulatory difficulty" and "selfcare difficulty" are separate in all ACS surveys, they were asked in a single question for the 2000 decennial long form. For consistency, they were combined into a single "any ambulatory or selfcare difficulty" variable. The variables "any hearing difficulty" and "any vision difficulty" were also available separately after 2007 but were combined into a single "any hearing or vision difficulty" variable for consistency.

outcomes are represented by Y_{ct}; while θ_c and $\delta_{s(c)t}$ respectively represent birth county and state-by-birth-cohort fixed effects; and X_{ct} contains a vector of covariates including sex, age, race, and survey year. Although not necessary for identification, the controls for sex, age, race, and survey year are included to increase precision.

Recent literature has shown that, in settings with staggered adoption, the two-way fixed effects approach in Equation 1 requires the strong assumption of homogeneous treatment effects to remain unbiased (Goodman-Bacon, 2018; Sun and Abraham, 2020; Chaisemartin and d'Haultfoeuille, 2020). Specifically, in the naïve application of Equation 1, the coefficient β in represents the weighted average of all 2x2 comparisons between counties in my sample. This includes comparisons where previously treated counties are used as controls for later treated counties, despite the fact that these "control" counties are still being affected by dynamic treatment effects themselves. If there are any heterogeneous treatment effects between counties that are treated at different points in time, those differences in the average treatment effect or the dynamic path of treatment effects over time are not accounted for and instead introduces bias into the estimated effects.

In the setting of water fluoridation, heterogeneous treatment effects are likely for a variety of reasons. The prevalence of other sources of fluoride from dental treatments, food, and toothpaste have changed over the many years of birth cohorts included in this sample. Changing access to dental care over time or generational differences in the importance of dental health could also drive heterogeneous treatment effects. Additional heterogeneity comes from the fact that fluoride is adopted at the public water system level and many counties have multiple public water systems as well as individuals who consume drinking water from private wells. This means that the fraction of a county's population receiving fluoridated water after initial adoption varies significantly across counties which strongly suggests heterogenous county treatment effects as a result. Given the high potential for heterogeneous treatment effects, it is necessary to adjust Equation 1 to ensure that treated counties are only compared to "clean" controls—counties without any treatment effects within the event window. I do this by implementing a stacked design that is robust to heterogeneous treatment effects (Cengiz et al., 2019). For any given year of initial treatment, only counties that are untreated through the end of the treatment window are valid controls, while previously or soon-to-be treated counties must be excluded from the control group.[20] This means that the control group changes over time, shrinking as each treated county is removed from the pool of potential controls for counties treated in later years. Because the same county must be included as a control unit, treated unit, or excluded from the comparison depending on the year of initial treatment, I create a separate dataset every year that any county first began water fluoridation. Within each dataset, occasionally referred to as "stacks" in the remainder of the paper, I generate time variables relative to year of initial treatment for treated groups within that stack as well as a variable indicating the year of initial treatment for that stack. Then, each of these treatment datasets are appended or "stacked" together. In the last three rows, Table 1 displays both the original number of collapsed county-birth-cohort observations as well as the total number of observations after the duplication and stacking procedure.

The stacked design prevents early fluoride adopters from acting as controls for counties that adopted fluoride later. The resulting estimates represent the unbiased average treatment effect even in the presence of heterogeneous treatment affects. The updated regression equation is:

$$Y_{ctg} = \theta_{cg} + \delta_{s(c)tg} + \mu X_{ct} + \beta(Exp6)_{ctg} + \epsilon_{ctg} \tag{2}$$

The key difference between this and the naïve two-way fixed effect approach in Equation 1 is the saturation of county and state-by-birth cohort fixed effects with g, indicating the dataset or stack that each observation originated from. Standard errors are clustered at

[20] I exclude from the control group any counties that are not-yet-treated but will be treated within the next eleven years. Given the definition of early childhood exposure from age 0-5, birth cohorts that experience any water fluoridation in their first five years of life are not clean controls but partially treated groups. Additionally, for both event studies and my primary estimates, the treatment window extends from birth cohorts born 15 years before through 6 years after the first year of fluoridation. As a result, any county that adopts water fluoridation within eleven years of the treated counties first water fluoridation would include partially treated birth cohorts within the event window and must be excluded from the control group.

the county level which both accounts for serial correlation over time as well as the repeated inclusion of the same county as a part of multiple stacks. To explore how fluoride exposure affects children of different ages, I will estimate an additional specification where ($Exp6$), the cumulative exposure measure, is replaced with a set of timing variables indicating the first year of water fluoridation relative to a person's birth. This dynamic difference-in-difference specification is as follows:

$$Y_{ctg} = \theta_{cg} + \delta_{s(c)tg} + \mu X_{ct} + \sum_{a=-6\,[a\neq 5]}^{15} \beta_a * 1[Fl_c - b = a] + \epsilon_{ctg} \tag{3}$$

In this specification, Fl_c and b represent the first year that an individual's birth county fluoridated their water and that individual's birth year. The timing variable a represents each individual's age in the first year of water fluoridation and covers the period from 6 years before birth through age 15 with age 5 as the omitted year. The dynamic treatment effects are captured in β_a and represent the effect of receiving fluoridated public water beginning at age a. All other terms are equivalent to those in Equation 1.

These event studies will show the net effects of first fluoride exposure at a particular age, which will include both the known benefits of fluoride exposure during tooth formation, as well as any negative cognitive or health effects that occur during the treatment window.[21]

5 Results

5.1 Primary Outcome Indices

I find that early childhood exposure to fluoride negatively impacts both health and labor market outcomes. I estimate the average intent-to-treat effect as a 0.45 percent of a standard deviation reduction in physical ability and health as well as a 0.69 percent of a standard deviation reduction in self-sufficiency; the effects are significant at the 1% and 10% level respectively. These results, as well as their robustness to alternative sets of control variables,

[21] It is worth noting that only county of birth is observed, not counties of residence throughout childhood. The likelihood of an individual residing in their birth county decreases over time, so estimates will be attenuated toward zero when estimating the effect of exposure in later years.

are shown in Table 2. Additional robustness checks are also described in Section 5.4 and shown in Table 4. These results are estimated using the county-birth-cohort specifications described in Section 4, and do not account for heterogeneity in the fraction of each county that is exposed to fluoride. Because counties may have multiple public water systems with different water fluoridation policies, and because some households source drinking water from private wells, not all individuals in a treated county will drink fluoridated water. This means that the estimates shown in Table 2 represent the intent-to-treat (ITT) effect, or the average treatment effect in county-birth-cohorts where anyone is exposed to fluoride. These estimates include individuals who were not exposed to water fluoridation and, as a result, understate the true effect of individual fluoride consumption. In order to approximate the average effect of treatment on treated (TOT) individuals, I divide the intent-to-treat effects by 0.37, the population weighted average percent of a county initially drinking fluoridated water.

These TOT estimates imply that drinking fluoridated water during early childhood causes a 1.9 percent of a standard deviation decrease in adult economic self-sufficiency and a 1.2 percent of a standard deviation decrease in physical ability and health. To put the magnitude of these results in context, I compare them to Bailey et al. (2020) who estimated the beneficial effects of early childhood access to food stamps using two nearly identical indices constructed from a similar dataset. While Bailey et al. (2020) found no statistically significant effects on physical ability and health, they found meaningful benefits for adults' economic self-sufficiency. Taking point estimates at face value, my findings suggests that early childhood fluoride exposure has the potential to erase approximately two-thirds of the self-sufficiency gains from early childhood utilization of food stamps.

One alternative method to account for county level differences in the percent of treated individuals within a county is to directly incorporate this variation into the definition of treatment. In this case, Equations 2 and 3 from Section 4 are adjusted so that the treatment variables ($Exp6_{ctg}$ and $1[Fl - b = a]$ respectively) are divided by the fraction of the county receiving fluoridated public water during the initial treatment period. Essentially, this inflates each county's estimates by the fraction of that county that was treated, rather than inflating the average intent to treat estimate by the average treatment percentage across all counties. Table 5 presents these alternative results for both primary outcomes and shows the robustness of these results to various sets of control variables. This method increases the precision of the estimated effects, with effects on both primary indices significant at the 1% level. The estimated 2.0 percent of a standard deviation impact on self-sufficiency is nearly identical to the previously estimated 1.9 percent. The estimated effect on physical ability and health however is only 0.7 percent of a standard deviation, smaller than the 1.2 percent estimated previously.[22]

I also estimate dynamic effects relative to a birth-cohort's age at the time of initial water fluoridation in their county. These event studies are shown in Figures 3 and 4. These figures show level effect sizes across birth cohorts with exposed from birth, which is consistent with differences in cohorts exposed at later ages being driven by water fluoridation rather than some other factor. The slope of the estimated trend line among cohorts treated from birth is included in these figures; slopes closer to zero provide the strongest evidence in support of my identifying assumption. The observed shrinking of marginal effects at older ages is also consistent with existing theory and evidence, as described in Section 2, that fluoride is likely to have the strongest effect on young children. These figures are discussed further in Section 5.4.

These results show that fluoride has a net negative impact on health and labor market outcomes even at relatively low levels of exposure. Even at levels previously thought to be safe, the known tooth strengthening effect of fluoride are overwhelmed by negative impacts on other determinants of health and self-sufficiency.

[22]Unfortunately, this method may introduce bias if counties with different treatment intensities were on different outcome trajectories prior to treatment. For example, this may be the case if urban counties, where private well use is less common, have a higher percentage of individuals drinking fluoridated water and also income and employment trends that are improving faster than those in rural areas. Despite the increased precision of using this method, the result in Table 2 remain my preferred specification as outlined in the pre-analysis plan (Roberts, 2021).

5.2 Secondary Outcomes

I also explore the effect of childhood fluoride exposure on high school graduation, incarceration, military service, and mortality. These results are shown in Table 3. I find statistically significant decreases in high school graduation and military service as well as increases in rates of adult incarceration. These effects translate to TOT effects of a 1.5 percentage point decrease in high school graduation, a 0.4 percentage point increase in likelihood of being incarcerated, and 1.0 percentage point decrease in military service. To once again frame effect sizes relative to Bailey et al. (2020), these point estimates, taken at face value, suggests that early childhood fluoride exposure has the potential to erase four-fifths of the decrease in incarceration caused by early childhood utilization of food stamps.[23,24] Point estimates also suggests increases in mortality, measured by a decrease in the likelihood of survival to 2020, but this effect is only statistically significant for men.[25]

I also estimate dynamic effects on each secondary outcome relative to a birth-cohort's age at the time of initial water fluoridation in their county and these results are shown in Figures 5-8. As discussed previously, near zero slopes on the left-hand side of the figures show consistently sized effects across birth cohorts with equal exposure to fluoride; consistent effects for cohorts with equal treatment exposure supports the assumption that differences in that outcome by exposure age are being driven by water fluoridation rather than some other factor. The impact on high school graduation is shown in Figure 5 and clearly shows that birth cohorts with the most fluoride exposure have the lowest rates of high school graduation. Additionally, the effects are concentration during early childhood (age 0-5) showing that exposure during those years has the largest impact on educational attainment. These results are consistent with the hypothesis that early fluoride exposure negatively impacts cognitive development.

[23] Similar comparisons of high school graduation and military service are not possible because equivalent outcomes are not included in Bailey et al. (2020)'s study of food stamps.

[24] In similar work, Barr and Smith (2021) find that each additional year of food stamps access reduces the likelihood of a criminal conviction in young adulthood by 2.5%.

[25] The TOT effect on men is a 0.3 percentage point decrease in the likelihood of surviving to 2020.

The interpretation of impacts on military service, as shown in Figure 7, are less clear. While level effects for fully exposed individuals supports the identifying assumption, the effects on military service are concentrated on later years, from age 5-9. Because these are estimates of the net effect of fluoride including potential health risk as well as improvements in dental health, it is difficult to distinguish what mechanism drives this pattern of effects.[26]

While estimated increases in incarceration rates are meaningfully large, the event study in Figure 6 shows that this trend exists even among cohorts that were exposed from birth despite the fact that these cohorts have equal levels of fluoride exposure. This suggests that, of the outcomes included in this study, my identifying assumption is least likely to hold in the case of incarceration effects; effects on incarceration should be interpreted with an additional degree of caution.

5.3 Replating Glied and Neidell (2010)

In prior work leveraging the county level adoption of water fluoridation policies, Glied and Neidell (2010) found that water fluoridation increased wages for women. These results were estimated using birth cohorts from 1957-1964 included in the National Longitudinal Survey of Youth (NLSY79).[27] I replicate their analysis using my sample. Specifically, I redefine treatment to match their definition (average fraction of county exposed to water fluoridation during an individuals first five years of life), and add controls for 1960 county characteristics, state fixed effects, and fluoride exposure as an adult.[28,29] These results, for

[26]Anecdotally, military service is known for providing high quality medical and dental care, such that marginal individuals may explore the option of military service while seeking dental treatment. If this is the case, then improvements in dental health may reduce military service. On the other hand, negative cognitive affects have an ambiguous impact on military service. While some individuals who opt out of additional education may turn to military service as an alternative, others who may have served in the military in the absence of fluoride exposure might be excluded if they are unable to pass military entrance requirements. Determining the interactions of these mechanisms at each age is beyond the scope of this study.

[27]Differences between their model and my own are described in more detail in Section 2.

[28]This is not an exact replication of their approach, as the NLSY includes numerous individual level variable that are not available in the ACS or decennial surveys. I also do not control for other county level variables included in their analysis, such as health care and investment measures, as these controls had very little impact on their estimates.

[29]This analysis is conducted on a clean version of the ACS and decennial surveys without any of the transformation used to collapse the data to the county-birth-cohort level or "stacking" used in my preferred specification.

the full sample as well as by gender, are shown in Table 7. Contrary to the results found using the NLSY, I estimate negative effects on wages for both genders. While these effects are only statistically different from zero at the 10% level, they are sufficient to reject, at the 5% level, the positive effects estimated by Glied and Neidell (2010) for both the full population and female only samples.[30]

To explore how sample size affects the estimated results, I also repeatedly draw 1000 random samples equal to the sample sizes used by Glied and Neidell (2010).[31] I estimate treatment effects separately within each random draw following their estimation model. Figures 9, 10, and 11 show histograms of these results, for the full sample as well as by gender. Each histogram also includes a line indicating the effect size estimated by Glied and Neidell (2010) in their equivalent sample. While their model predicts negative effects of fluoride on wages in the Census sample, these figures show that a non-trivial portion of small sample estimates are positive. This suggests that positive effects found by Glied and Neidell (2010) may be the result of their relatively small NSLY sample being a similar outlier.[32,33,34]

5.4 Testing Identifying Assumption

The key identifying assumption is that, conditional on birth cohort and county fixed effects, the non-fluoride factors that influence an individuals' long run health and labor market outcomes are orthogonal to the presence or level of community water fluoridation in their county of birth at a particular age. This means that, conditional on birth cohort and county fixed effects, any difference in outcomes among those exposed to fluoridated water is the

[30] Glied and Neidell (2010) estimate small negative effects on men, which is not statistically different from my estimates.

[31] While their sample consists of roughly 12,000 individuals, they observe these individuals multiple time resulting in observation counts of 37,098 in the male only sample, 35,297 in the female sample, and 72,395 in the combined sample. I separately draw 1000 random samples equal to the respective observation counts from each of three groups.

[32] This is consistent with evidence found by Ioannidis, Stanley and Doucouliagos (2017) on the use of underpowered samples.

[33] It is also possible that these differences are simply a result of failing to exactly match the model used by Glied and Neidell (2010), specifically that my estimation does not contain the breadth of individual level controls included in their study.

[34] This difference is not the result of different sample periods. An alternative version of this replication procedure restricted the sample to the same birth cohorts used by Glied and Neidell (2010) (1957-1964) and found statistically significant negative effects of an even larger magnitude.

result of the fluoride itself and not any other factor. In this setting, the main assumption is that the shift in health and labor market outcomes of untreated individuals across time effectively proxies for the shift in outcomes that would have occurred for individuals drinking fluoridated water in the absence of fluoride treatment. It is impossible to observe the counterfactual outcomes of individuals exposed to water fluoridation, but I conduct several tests to explore how likely this assumption is to hold.

Water fluoridation is endogenously determined at the local level. One potential threat to my identifying assumption is if communities that implemented water fluoridation had outcomes that were already trending away from untreated communities at the time of fluoride adoption; this would violate parallel trends. To explore the relationship between county characteristics and the timing of decisions to adopt water fluoridation, I estimate the impact of various 1960 county characteristics on the binary decision to ever adopt fluoride as well as the timing of that fluoride adoption. These results are shown in Table 8. I find that the decision to add fluoride is positively correlated with population, urbanicity, homeownership and education but negatively correlated with the percent of a county that voted (in the prior election) and the percent living in rural areas.

Column 2 of Table 4 present the result where the sample is restricted to exclude counties that never adopt water fluoridation. This has little impact on estimated effects, suggesting that my results are not driven by differential trends between treated and never treated counties. Additionally, among counties that adopted water fluoridation, urban counties adopted fluoride earlier while counties with a high percentage of the population under the age of five tended to adopt fluoride later. It is worth noting that these differences in the levels of observable characteristics are not a threat to the internal validity of my results unless they also correspond to differential trends between treatment and control counties in my outcome variables. Column 3 of Table 4 shows the results of including these predictors interacted with linear time trends as controls while estimating the effect of fluoride exposure on my primary outcomes.[35] While point estimates remain negative for both outcomes, effects on physical ability and health are diminished and lose statistical significance.[36]

I explore the evidence of the parallel trends assumption by generating even studies for each outcome. As shown in Equation 3, I estimate dynamic effects relative to a birth-cohort's age at the time of initial water fluoridation in their county. If treatment and control groups have differential trends unrelated to fluoride treatment, then we would expect individuals born after the beginning of water fluoridation to continue to trend apart despite the fact that water fluoridation is not changing for these groups.[37] On the other hand, consistently sized effects for these birth cohorts would provide suggestive evidence that the identifying assumption holds for that outcome. The slope of the estimated trend line among fully treated cohorts is displayed in Figures 3-8 as evidence for each respective primary and secondary outcome; slopes closer to zero provide the strongest evidence in support of my identifying assumption. Additionally, because treatment is likely to have the strongest effect on young children, a leveling off of treatment effects at older ages, due to smaller marginal impacts of fluoride exposure during later development periods, is consistent with differences being driven by water fluoridation rather than some other factor.

My identifying assumption also might also fail if there are meaningful shifts in the composition of people being born into treated and untreated counties across the sample period. This would occur if demographic shifts between counties happened simultaneous to water fluoridation or if individuals migrate between counties in response to water fluoridation. Aggeborn and Öhman (2017) suggest that migration in response to water fluoridation is unlikely because fluoride in water is colorless, odorless, and tasteless, meaning that changes in water fluoridation are not salient to the affected populations. Additionally, decisions regarding

[35] Only 1960 county characteristics that have a statistically significant relationship (at the 10% level) with the timing of water fluoridation are included in this linear trends specification.

[36] Given the cumulative nature of the impact of fluoride over time, it is possible that these linear trends are overfitting and absorbing some of the true impact of fluoride as well.

[37] While presence of water fluoridation is not changing, there may be changes in the fraction of a county that is treated during this time period, but these changes are relatively small on average and unlikely to drive any differential trends.

water fluoridation are frequently made with little or no input from local residents, making it even more unlikely that water fluoridation levels are salient enough to drive migration across counties.[38] It is however still possible that migration patterns happened to coincide with water fluoridation. This test is particularly relevant, given that the great migrations of more than 6 million blacks from the rural south into urban cities continued through the 1950's and 60's, overlapping with a large portion of the fluoride variation included in this study.

I test for demographic shifts that correspond to race by estimating the effect of water fluoridation on race, gender, age at time of survey, and likelihood of living in birth county as an adult, as shown in Table 6. This test shows the timing of water fluoridation did coincide with changing racial demographics, specifically a 1.0 percentage point decline in the fraction of the population that was white. This means that counties that adopted fluoride also tended to outpace control counties in the rate at which racial diversity increased. While any causality between county migration and water fluoridation remains unlikely, it does appear that the timing of the great migration into urban areas coincided with the early adoption of water fluoridation in those counties as is shown in Table 8.

These differential trends in racial demographics are a threat to my identifying assumption if control counties are not a reliable counterfactual for treatment counties. I explore the impact of migration and its effect on my estimates in several ways. First, I estimate effects restricted to only white individuals. If my overall effects are driven by migration of non-white individuals around the time of water fluoridation, then restricting the sample to only include white individuals eliminates that source of variation and should result in shrinking effect sizes. In practice, comparing Column 1 in Table 4 to my primary results in Table 2 shows that effect sizes are nearly identical even when race is restricted to only white individuals.[39] While effects are much smaller in this sample than in Column 1 of Table 2 (estimates with

[38]While some referendums were held allowing individuals to vote on community water fluoridation, roughly two-thirds of early water fluoridation decisions were made by government administrators without citizen input (Crain, Katz and Rosenthal, 1969).

[39]Migration may still affect the outcomes of individuals in this sample indirectly through changing peer groups and county characteristics, but I expect these effects to be relatively small compared to potential direct effect of a changing sample.

no controls), they are quite similar to estimated effects in the full sample when race fixed effects are included, suggesting that these fixed effects are already controlling for any key differences between current county residents and migrating racial groups.

While the balance tests only show statistically significant changes in the racial makeup of counties at the time treatment, it is possible that there are changes to other unobservable characteristics that coincide with the timing of water fluoridation. In order to account for general patterns of migration I also estimate effects on my primary outcomes while restricting the sample to only include individuals with strong geographic roots, measured by an individual living in their birth county at the time of their adult survey.[40,41] Additionally, I create a county level measure of both in- and out-migration where in-migration is defined as the fraction of individuals surveyed in a county who were not born there and out-migration is defined as the fraction of individuals born in that county who are not surveyed there as adults. I create several samples, restricting to counties with progressively lower levels of both in- and out- migration rates. These estimates are shown in Table 4 columns 5-7 and represent counties with both in- and out-migration levels below the 90th, 75th, and 50th percentiles respectively. The magnitude and statistical significance of estimates remains consistent across these migration cuts. These results suggest that while significant migration did occur during my sample period, and even coincided with the timing of water fluoridation for some groups, migration is unlikely to be a primary driver of the estimated effects of water fluoridation.

6 Conclusion

Tooth decay is one of the most common chronic childhood diseases in the United States and one in four children below the poverty line have untreated tooth decay (Newacheck

[40]It is still possible that birth cohorts were changing over time as a response to the migration of their parent's generation. But, to the extent that first generation residents of a county are less likely to remain in county through adulthood, this measure still captures a sample that is ex-ante less likely to be affected by migration effects.

[41]This sample also serves the dual purpose of focusing on individuals who likely lived in their birth county throughout childhood, removing noise in the treatment variable caused by moving during childhood.

et al., 2000; Dye, Li and Thornton-Evans, 2012). Water fluoridation has been promoted since 1945 as a simple, cost effective, and egalitarian approach to improving dental health. Today, over 70% of publicly supplied drinking water in the United States is fluoridated. But, despite strong evidence that exposure to low levels of fluoride are an effective way to strengthen teeth, recent evidence has suggested that fluoride may negatively affect cognitive ability even at these low levels (Choi, Zhang and Grandjean, 2012; Grandjean, 2019). On the other hand, recent studies within economics have also found that childhood exposure to water fluoridation improves adult labor market outcomes (Glied and Neidell, 2010; Aggeborn and Öhman, 2017).

In this paper, I use U.S. Census data linked to childhood fluoride exposure to provide large sample quasi-experimental evidence of the long run health and labor market effects of community water fluoridation programs. This data includes both respondents to the long form 2000 decennial census as well as American Community Survey respondents from 2001 to 2016. I generate a physical ability and health index as well as a self-sufficiency index and estimate the effect of childhood exposure to water fluoridation on these outcomes as well as the secondary outcomes of high school graduation, military service, incarceration, and mortality.

I find that children exposed to community water fluoridation from age zero to five experience a 1.9 percent of a standard deviation decrease in their adult economic self-sufficiency, 1.2 percent of a standard deviation decrease in adult physical ability and health, as well as a 1.5 percentage point decrease in high school graduation, a 1.0 percentage point decrease in military service, and a 0.4 percentage point increase in likelihood of being incarcerated. These results show, even at levels previously thought to be safe, the net effect of fluoride is negative.

These findings have important implications for water fluoridation policy. Fluoride is still being added to a majority of public water supplies in the U.S. and regulations for regions with naturally high levels of fluoride allow water to carry up to 4 mg/L, four times the level of water fluoridation evaluated in this study. The results of this study demonstrate the need for a re-evaluation of water fluoridation policies. The observed negative impacts of fluoride combined with widespread access to the enamel strengthening benefits of fluoride through toothpaste and dental treatments provides a strong argument for ending the practice of water fluoridation and lowering the maximum levels of fluoride allowed by safe drinking water standards. If water fluoridation practices continue, more research is needed to determine the optimal level of fluoride such that the marginal benefits to dental health are not overwhelmed by impacts on health, cognitive ability, and labor market success. Further study is needed to determine the exact biological mechanisms that are driving these negative effects and discover solutions that mitigate them.

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7 Tables

Table 1: Summary Statistics

	(1) Full Sample	(2) Men	(3) Women	(4) Treated Counties	(5) Never Treated
Demographics					
White	0.876	0.886	0.866	0.871	0.882
Male	0.480	1	0	0.478	0.482
Age	51.82	51.69	51.93	54.88	48.38
Resides In Birth County	0.164	0.167	0.162	0.167	0.162
Physical Ability and Health Index					
No Ambulatory Difficulty	0.921	0.927	0.915	0.909	0.933
No Cognitive Difficulty	0.953	0.952	0.953	0.949	0.956
No Independent Living Difficulty	0.944	0.948	0.939	0.937	0.951
No Hearing Or Vision Difficulty	0.971	0.967	0.975	0.968	0.975
Self-sufficiency Index					
In Laborforce	0.698	0.759	0.641	0.658	0.742
Worked Last Year	0.736	0.792	0.684	0.699	0.778
Average Weekly Work Hours	29.11	33.38	25.18	27.56	30.85
Weeks Worked Last Year	10.84	11.93	9.830	9.570	12.27
Labor Income	39460	53410	26600	38140	40950
Other Income	3359	4232	2553	3860	2796
Percent Of Poverty Level	351	360	342	354	347
Not In Poverty	0.920	0.932	0.909	0.922	0.918
Welfare Income	46	34	57	40	53
Social Security Income	230	224	236	249	209
Other Outcomes					
Incarcerated	0.008	0.015	0.001	0.006	0.01
Veteran	0.158	0.300	0.027	0.178	0.135
Graduated High School	0.860	0.848	0.870	0.854	0.867
Currently Married	0.686	0.718	0.656	0.688	0.684
Survived To 2020	0.944	0.934	0.953	0.931	0.958
Sample (Cells)	32,660,000	15,890,000	16,770,000	15,370,000	17,290,000
Unique Piks	29,150,000	13,860,000	15,300,000	24,850,000	4,296,000
Collapsed Cells	3,493,000	1,668,000	1,825,000	2,087,000	1,406,000

Note: This table shows summary statistics for the primary sample in column (1) with additional summary statistics by gender in columns (2-3) and by county treatment status in columns (4-5). Summary statistics for the component parts of the primary two outcome indices are listed separately. The number of observations included in each regression (after collapsing and duplicating data as described in the analysis section) is included as "Sample (Cells)".

Table 2: Main Outcomes - By Gender

	(1)	(2)	(3)	(4)	(5)
Full Sample					
Physical Ability and Health Index	-0.0064***	-0.0046***	-0.0046***	-0.0045***	-0.0045***
	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Self-sufficiency Index	-0.0099**	-0.0054	-0.0057	-0.0054	-0.0069*
	(0.0044)	(0.0038)	(0.0037)	(0.0037)	(0.0037)
Observations	32,660,000	32,660,000	32,660,000	32,660,000	32,660,000
Women Only					
Physical Ability and Health Index	-0.0063***	-0.0043***	-0.0043***	-0.0042**	-0.0042***
	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Self-sufficiency Index	-0.0066	-0.0032	-0.0032	-0.0029	-0.0041
	(0.0045)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Observations	16,770,000	16,770,000	16,770,000	16,770,000	16,770,000
Men Only					
Physical Ability and Health Index	-0.0066***	-0.0049***	-0.0049***	-0.0047***	-0.0048***
	(0.0018)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Self-sufficiency Index	-0.0138***	-0.0083**	-0.0083**	-0.0080**	-0.0099**
	(0.0048)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Observations	15,890,000	15,890,000	15,890,000	15,890,000	15,890,000
Race FE	N	Y	Y	Y	Y
Gender FE	N	N	Y	Y	Y
Survey Year FE	N	N	N	Y	Y
Age FE	N	N	N	N	Y

Note: This table displays the primary index outcomes as additional controls are added - ending with the preferred specification in column (5). Results are also shown separately by gender. Observations refers to the number of observations used in each regression, after the after the collapsing and duplication procedures outlined described in the analysis section. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

Table 3: Secondary Outcomes

	(1) HS Diploma	(2) Incarcerated	(3) Alive in 2020	(4) Veteran
Full Sample	-0.0054***	0.0015***	-0.0006	-0.0038***
	(0.0014)	(0.0003)	(0.0004)	(0.0011)
Observations	18,890,000	22,970,000	32,660,000	32,660,000
Women Only	-0.0048***	0.0003***	-0.0001	-0.0002
	(0.0014)	(0.0001)	(0.0004)	(0.0003)
Observations	9,708,000	11,800,000	16,770,000	16,770,000
Men Only	-0.0061***	0.0027***	-0.0011**	-0.0079***
	(0.0016)	(0.0005)	(0.0005)	(0.0021)
Observations	9,183,000	11,170,000	15,890,000	15,890,000

Note: This table displays a set of secondary outcomes with each column representing a different outcome and subsequent rows presenting results separately by gender. Observations refers to the number of observations used in each regression, after the after the collapsing and duplication procedures outlined described in the analysis section. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

Table 4: Robustness Checks

	(1) White	(2) Ever Treated Counties	(3) Linear Time Trends	(4) Reside in Birth County	(5) Lowest 90% Migration	(6) Lowest 75% Migration	(7) Lowest 50% Migration
Physical Ability & Health Index	-0.0046***	-0.0049***	-0.0016	-0.0054**	-0.0042***	-0.0050***	-0.0052***
	(0.0014)	(0.0017)	(0.0015)	(0.0022)	(0.0015)	(0.0016)	(0.0019)
Self-Sufficiency Index	-0.0046	-0.0047	-0.0063*	-0.0106**	-0.0095*	-0.0101**	-0.0076**
	(0.0034)	(0.0037)	(0.0038)	(0.0052)	(0.0038)	(0.0042)	(0.0043)
Observations	24,360,000	15,370,000	32,040,000	17,390,000	27,730,000	19,800,000	9,487,000

Note: This table shows results from various robustness checks with each column representing a separate specification and the two rows showing the effect on the two primary outcomes. Column (1) restricts the sample to white individuals. Column (2) restricts the sample to only include counties that were eventually treated within the treatment window. Column (3) shows the results from including demographics controls for each county interacted with linear time trends. Column (4) restricts the sample to only include individuals who resided in their birth county at the time of their survey. Columns (5-7) restrict the sample to exclude counties with high levels of migration. County level migration is defined in two different ways. First, as the fraction of individuals born in a county who were surveyed elsewhere as an adult and secondly as the fraction of adults living in a county who were not born there. Counties with migration rates above the 50th, 75th and 90th percentile in either measure were excluded from the respective samples. Observations refers to the number of observations used in each regression, after the after the collapsing and duplication procedures outlined described in the analysis section. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

Table 5: Main Outcomes - Adjusted by Percent of County Treated

	(1)	(2)	(3)	(4)	(5)
Full Sample					
Physical Ability and Health Index	-0.0117***	-0.0069***	-0.0069***	-0.0067***	-0.0069***
	(0.0026)	(0.0024)	(0.0024)	(0.0025)	(0.0024)
Self-sufficiency Index	-0.0292***	-0.0173**	-0.0175**	-0.0171**	-0.0200***
	(0.0085)	(0.0072)	(0.0071)	(0.0072)	(0.0072)
Observations	32,660,000	32,660,000	32,660,000	32,660,000	32,660,000
Race FE	N	Y	Y	Y	Y
Gender FE	N	N	Y	Y	Y
Survey Year FE	N	N	N	Y	Y
Age FE	N	N	N	N	Y

Note: This table displays primary outcomes when the treatment variable has been adjusted to incorporate the fraction of county exposed to fluoride. Observations refers to the number of observations used in each regression, after the after the collapsing and duplication procedures outlined described in the analysis section. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

Table 6: Balance Tests

	(1) Age	(2) Male	(3) Resides in Birth County	(4) White
Balance Tests	0.0077	0.0003	0.0002	-0.0101***
	(0.0070)	(0.0007)	(0.0014)	(0.0026)
Observations	32,660,000	32,660,000	32,660,000	32,660,000

Note: This table displays the results of balance tests where my preferred stacked difference-in-differences design was used to estimate any changes in observable demographic characteristics that simultaneously with treatment. Observations refers to the number of observations used in each regression, after the after the collapsing and duplication procedures outlined described in the analysis section. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

Table 7: Replication of Glied and Neidell (2010)

	(1) Full Sample	(2) Female	(3) Male
Replication Results			
Log Wage	-0.0105*	-0.0076	-0.0125
	(0.0064)	(0.0068)	(0.0078)
Observations	19,320,000	10,140,000	9,179,000

Note: This table displays the results of replicating Glied and Neidell (2010) by estimating the effect of childhood exposure to water fluoridation on log hourly wages. The details of this replication are outlined in Section 7. Significance levels indicated by: * (p<0.10) **(p<0.05), ***(p<0.01).

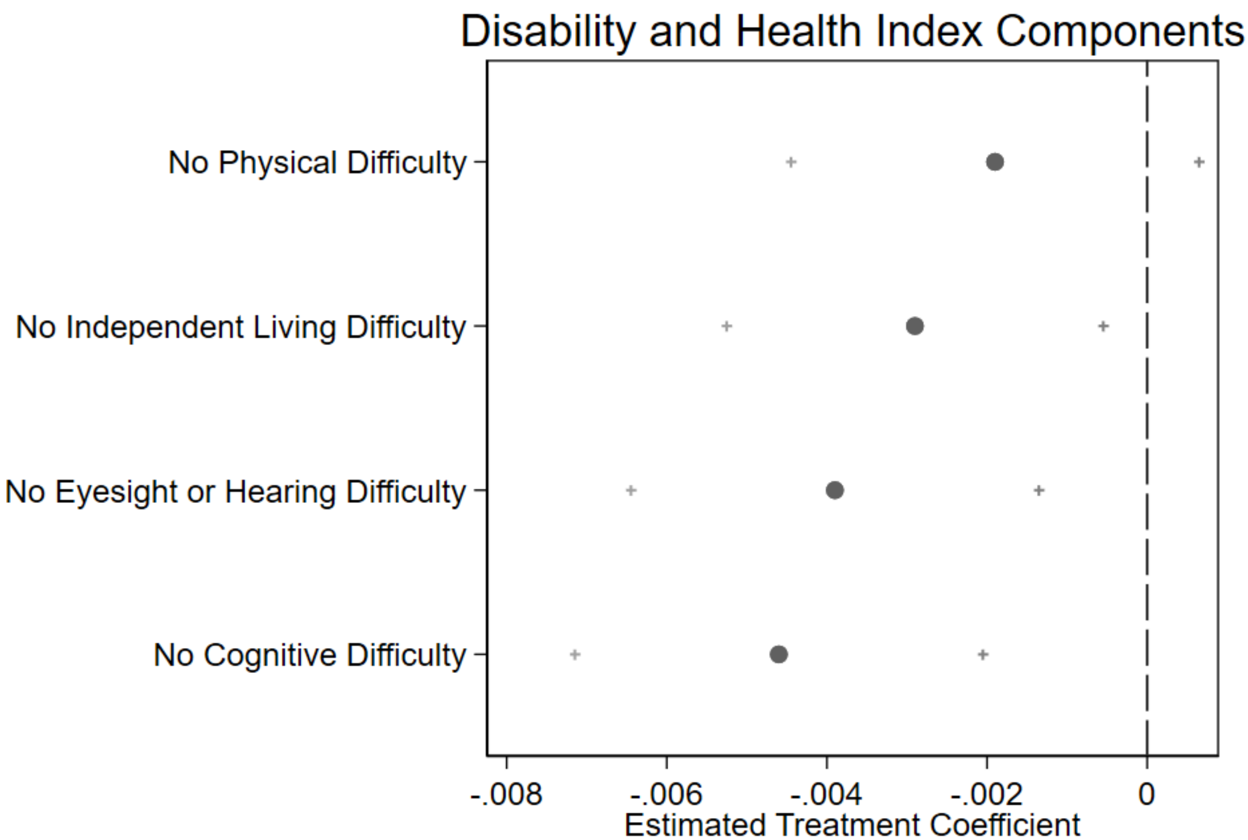
Table 8: Water Fluoridation and 1960 County Characteristics

	(1) Ever Treated	(2) Year of First Treatment
1960 County Characteristics		
Population (in 10,000's)	0.0016***	-0.0018
	(0.0001)	(0.8676)
Population Per Mile (in 1,000's)	-0.0018	0.1630
	(0.6822)	(0.1446)
10 Year Population Change (in 1,000's)	0.0284	-20.6297
	(0.9010)	(0.0917)
Percent in Urban Area	0.0012**	-0.0949***
	(0.0028)	(0.0000)
Percent in Rural Area	-0.0038***	-0.0200
	(0.0000)	(0.4673)
Percent Non-White	0.0014	0.0319
	(0.0974)	(0.2175)
Percent Under Age 5	-0.0177	0.8593**
	(0.0635)	(0.0052)
Percent Over Age 65	0.0095	0.3142
	(0.1590)	(0.1721)
Median Age	-0.0078	0.1359
	(0.1398)	(0.4175)
Median Income (in $1,000's)	-0.0103	-0.8151
	(0.5323)	(0.1676)
Median Years Education	-0.0321*	1.3249*
	(0.0143)	(0.0257)
Percent with Less Than 5 Years Education	-0.0078**	-0.0140
	(0.0011)	(0.8537)
Percent with High School Diploma	-0.0000	-0.1868*
	(0.5198)	(0.0185)
Death Rate	-8.9473	58.4335
	(0.1005)	(0.7600)
Marraige Rate	-1.1346	32.6536
	(0.1790)	(0.2263)
Employment Rate	-0.3762	-3.5741
	(0.1735)	(0.6838)
Percent Homeowners	0.6118***	-0.4737
	(0.0000)	(0.8851)
Percent Voted	-0.7391***	13.4338*
	(0.0000)	(0.0234)
Democratic Voteshare	0.0018*	-0.0248
	(0.0119)	(0.2541)
Household Size	-0.0559	2.7432*
	(0.1089)	(0.0105)
Observations	2988	2070

Note: This table shows the relationship between county characteristics and the endogenous decision to adopt water fluoridation. Column (1) shows the relationship between these county characteristics and a binary variable indicating if a county ever adopted water fluoridation (by 1992). Column (2) shows the relationship between county characteristics and the first year of fluoride adoption. Negative values indicate that those types of counties first adopted fluoride in earlier years. All regressions include state fixed effects. Significance levels indicated by: * ($p<0.10$) **($p<0.05$), ***($p<0.01$).

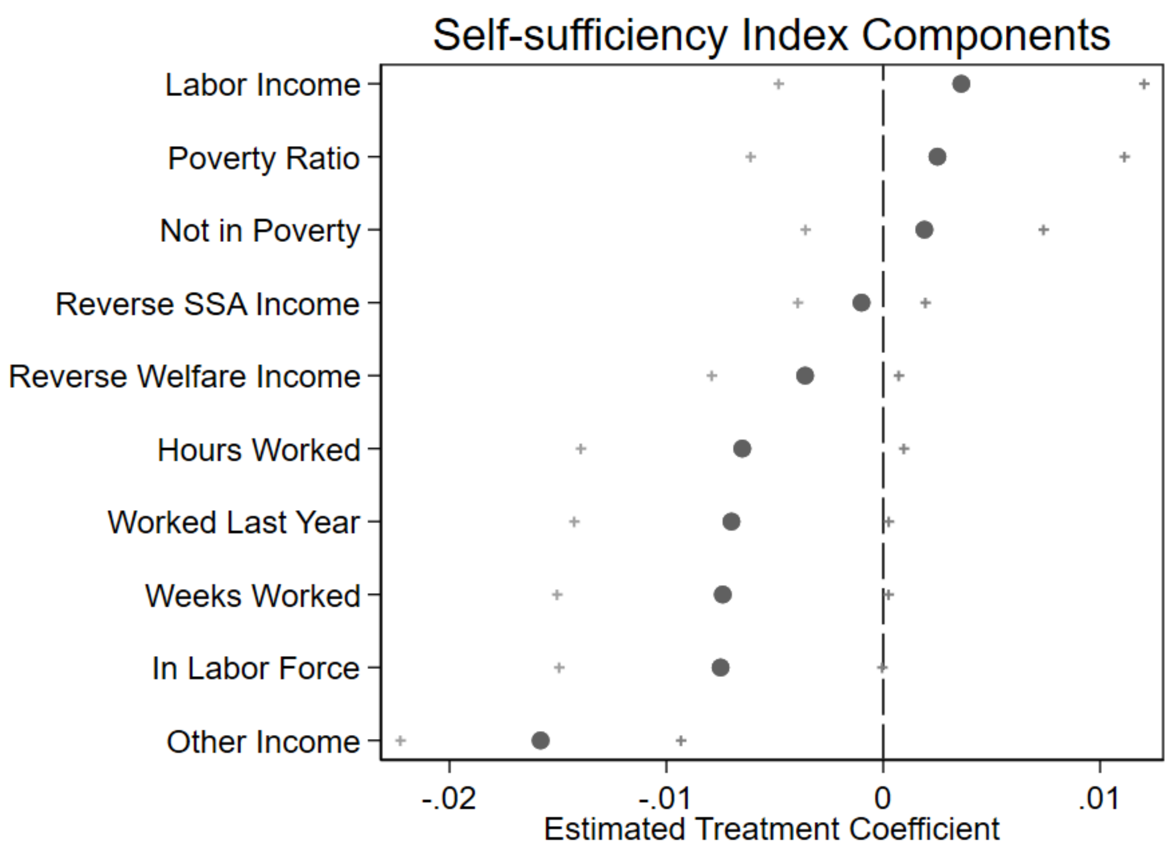
8 Figures

Figure 1



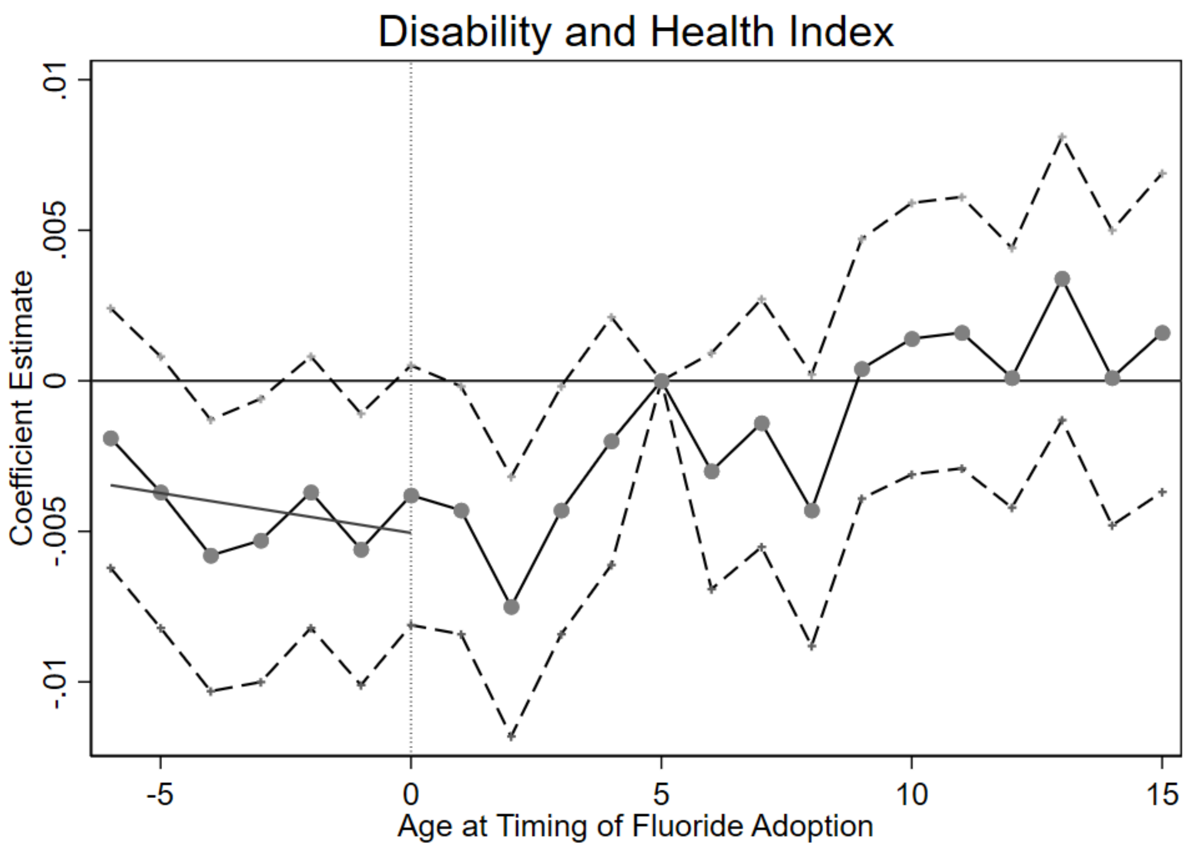
Note: This figure shows the estimated treatment effect on each (normalized) outcome included in the Disability and Health Index.

Figure 2



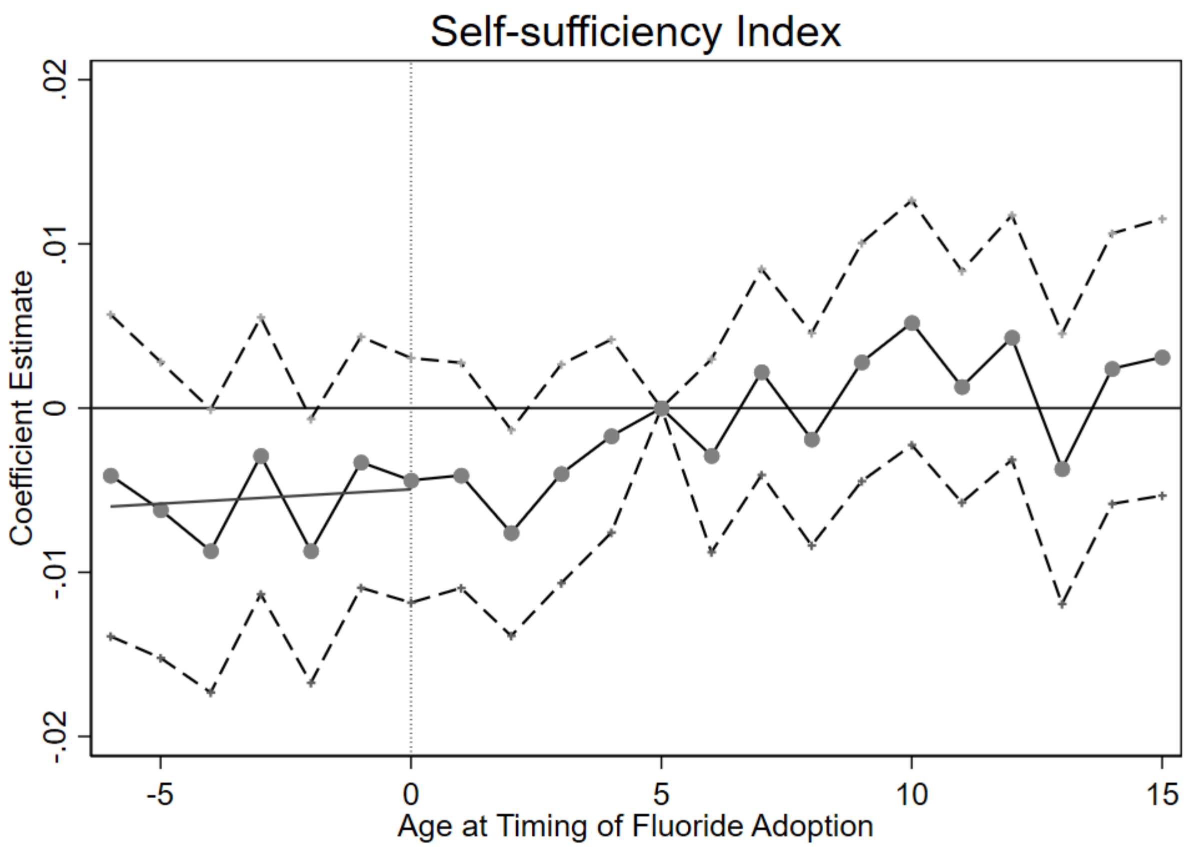
Note: This figure shows the estimated treatment effect on each (normalized) outcome included in the Self-sufficiency Index.

Figure 3



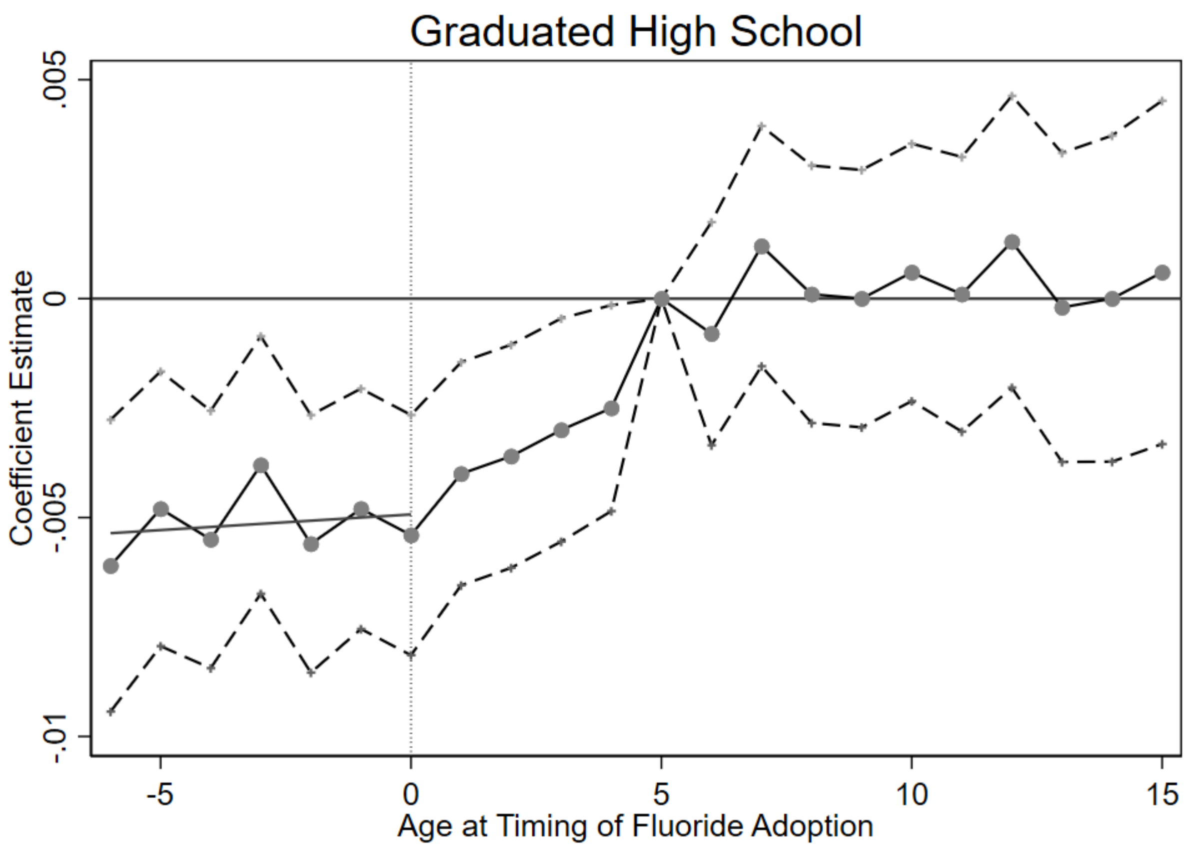
Note: This figure shows the dynamic effects of fluoride exposure on Disability and Health by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 4



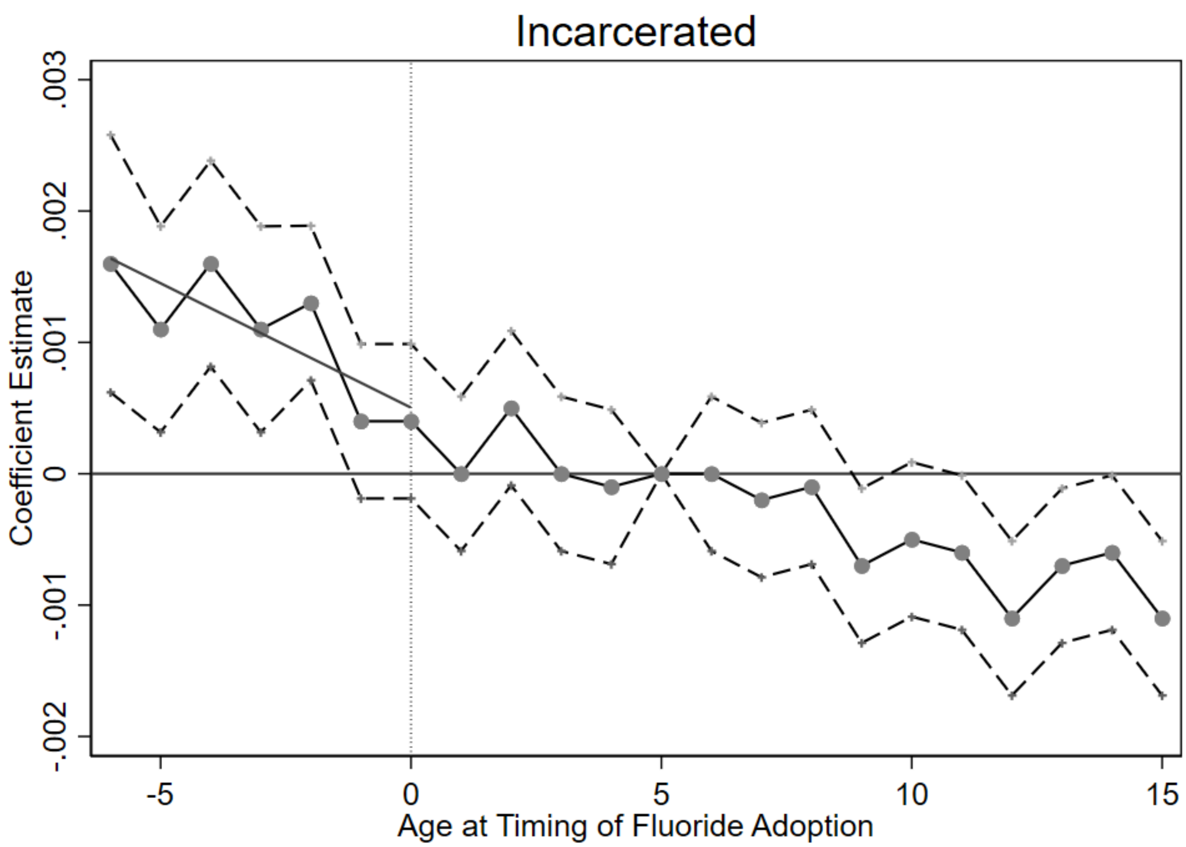
Note: This figure shows the dynamic effects of fluoride exposure on Self-sufficiency by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 5



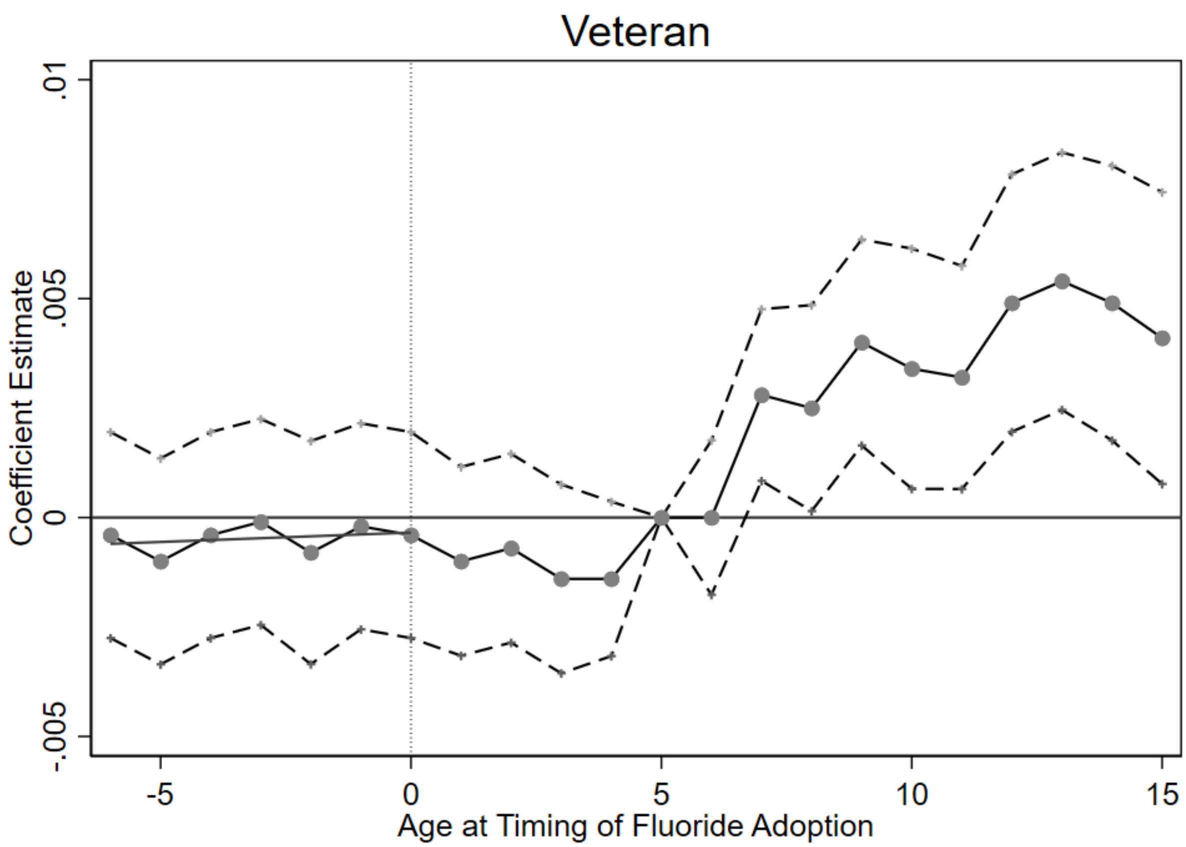
Note: This figure shows the dynamic effects of fluoride exposure on High School completion by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 6



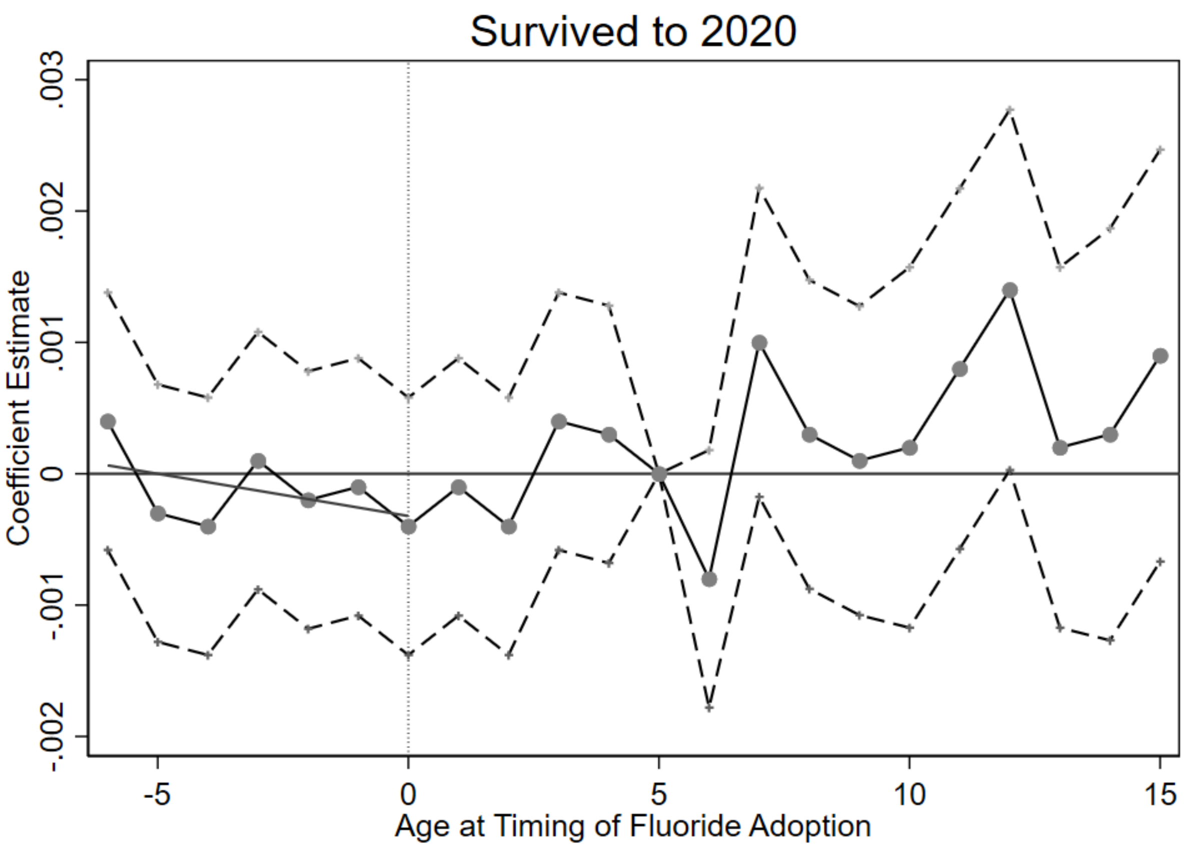
Note: This figure shows the dynamic effects of fluoride exposure on Incarceration by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 7



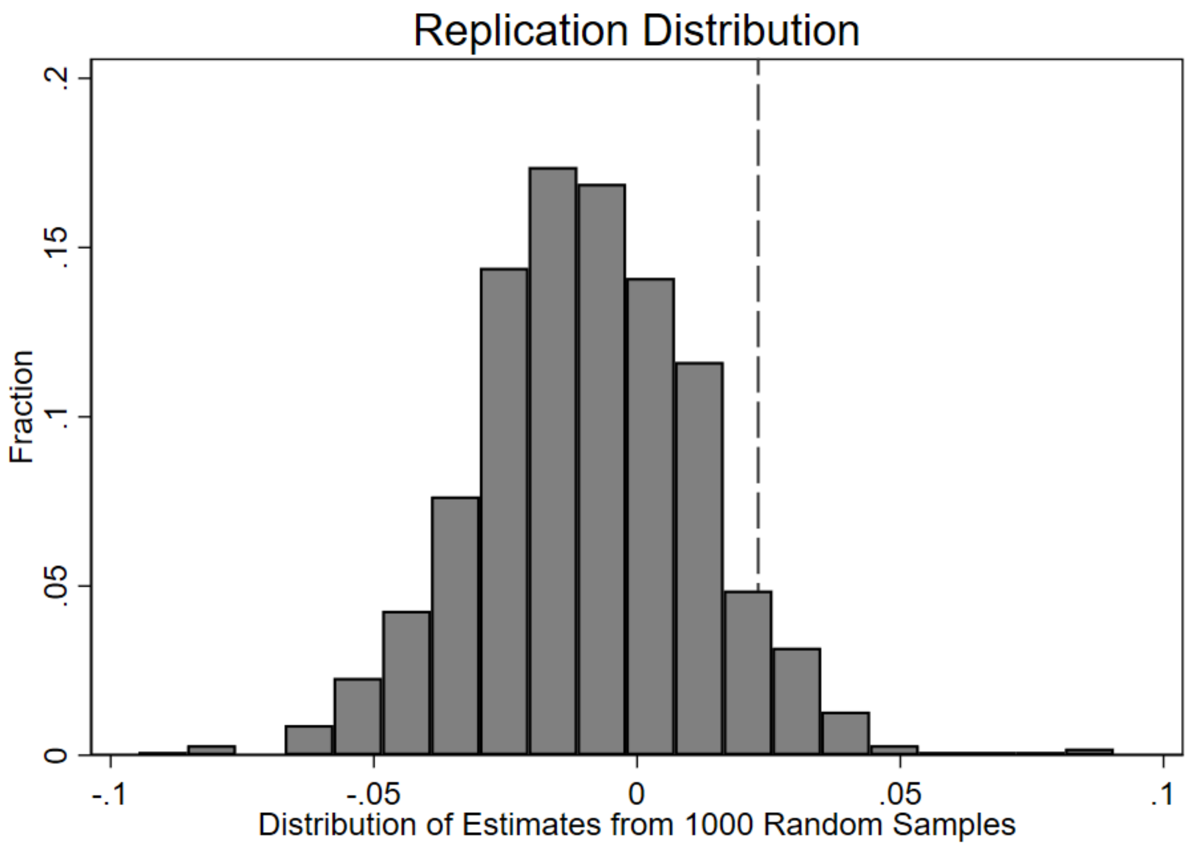
Note: This figure shows the dynamic effects of fluoride exposure on military service by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 8



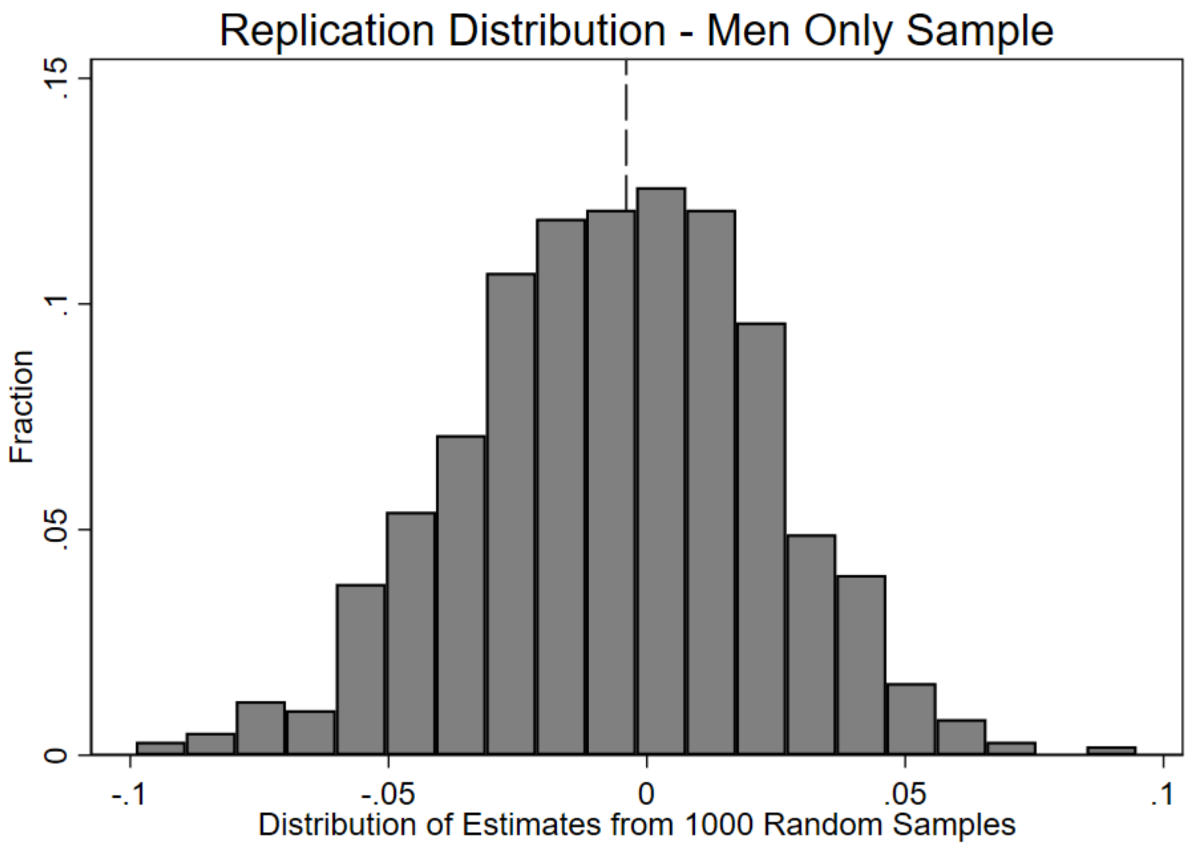
Note: This figure shows the dynamic effects of fluoride exposure on longevity by cohort age at the time of county fluoride adoption. Cohorts left of zero were born after fluoride adoption and were potentially exposed to fluoride for their entire childhood. Cohorts to the right of zero received less childhood exposure depending on their age when fluoride was first adopted.

Figure 9



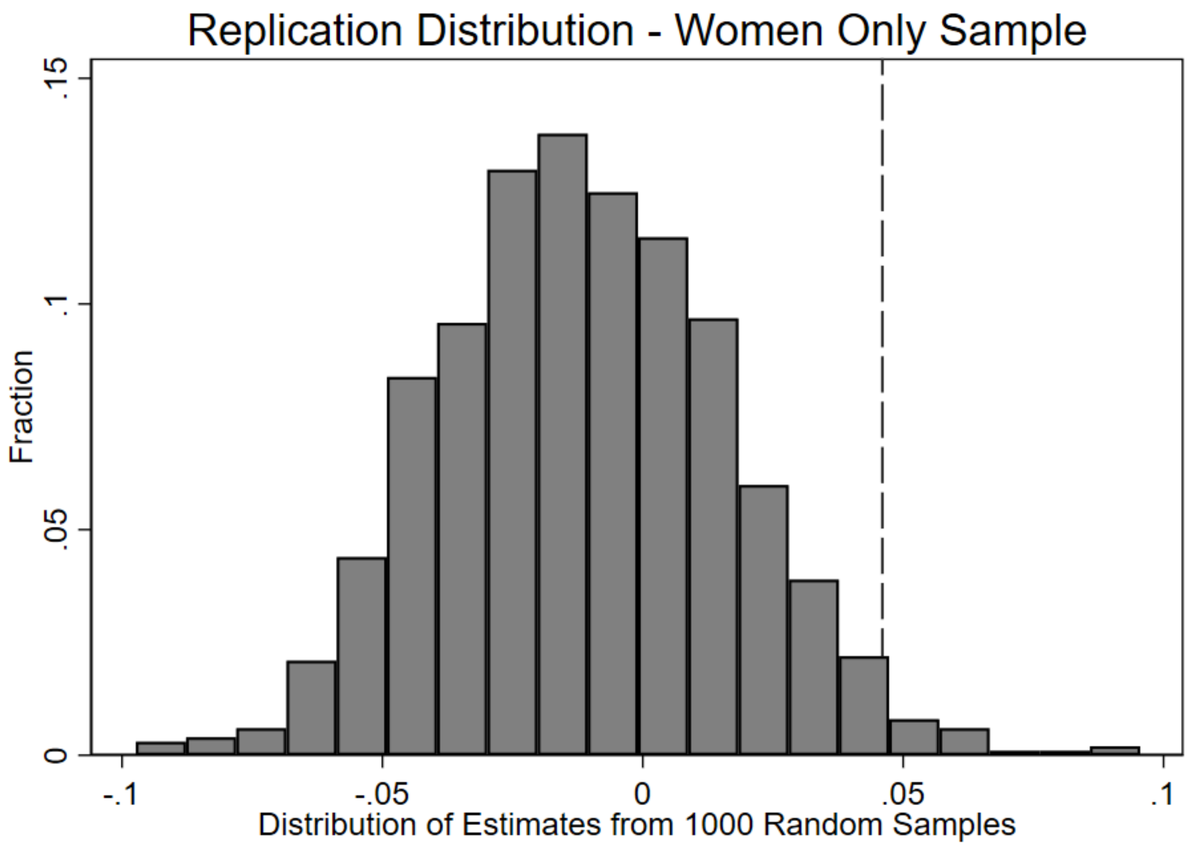
Note: This figure shows the distribution of estimates generated replicating Glied and Neidell (2010) with random 1000 random samples. The details of this replication procedure are described in Section **??**. The dashed line indicates the coefficient estimated by Glied and Neidell (2010).

Figure 10



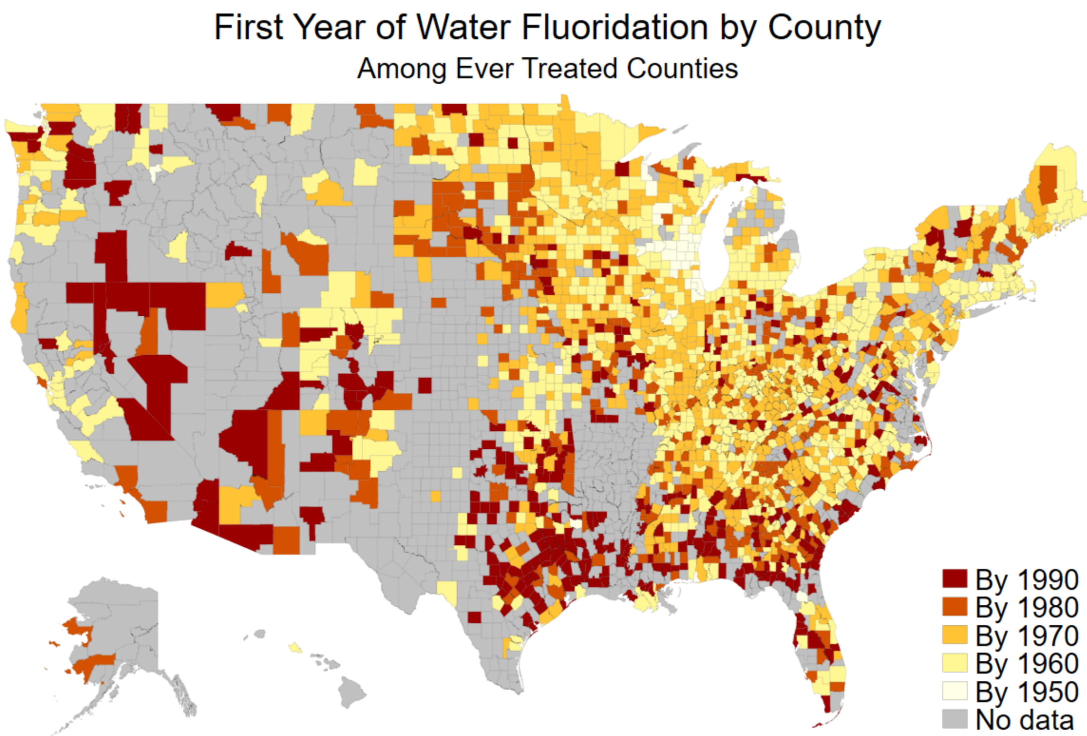
Note: This figure shows the distribution of estimates generated replicating Glied and Neidell (2010) with random 1000 random male only samples. The details of this replication procedure are described in Section **??**. The dashed line indicates the coefficient estimated by Glied and Neidell (2010) in their male only sample.

Figure 11



Note: This figure shows the distribution of estimates generated replicating Glied and Neidell (2010) with random 1000 random female only samples. The details of this replication procedure are described in Section **??**. The dashed line indicates the coefficient estimated by Glied and Neidell (2010) in their female only sample.

Figure 12



Note: This figure shows the timing of county level adoption of water fluoridation. Counties with missing water fluoridation data and never treated counties are included in the "no data" group.