The Effects of Fluoride in Drinking Water

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Water fluoridation is a common but debated public policy. In this paper, we use Swedish registry data to study the causal effects of fluoride in drinking water. We exploit exogenous variation in natural fluoride stemming from variation in geological characteristics at water sources to identify its effects. First, we reconfirm the long-established positive effect of fluoride on dental health. Second, we estimate a zero effect on cognitive ability in contrast to several recent debated epidemiological studies. Third, fluoride is furthermore found to increase labor income. This effect is foremost driven by individuals from a lower socioeconomic background.

We thank Erik Grönqvist, Eva Mörk, Matz Dahlberg, Mikael Elinder, Caroline Hall, Ronny Freier, Kaisa Kotakorpi, Martin Karlsson, Melanie Luhrmann, Mattias Nordin, and Adrian Adermon for helpful discussions, comments, and suggestions as well as Robin Djursäter, Liselotte Tunemar, Tomas Byström, Gullvy Hedenberg, and Louise von Essen. Moreover, we thank seminar participants at the Department of Economics at Uppsala University, Geological Survey of Sweden, U-CARE, the 72th International Institute of Public Finance conference in Lake Tahoe, the European Economic Association–European Meeting of the Econometric Society 2016 conference in Geneva, Institute for Evaluation of Labour Market and Education Policy (IFAU), Essen Health Conference 2017, and the Health Economic Forum at Uppsala University workshop in 2017. Last, we thank the editor James J. Heckman and four anonymous reviewers for constructive comments on our manuscript. This research project is based at the IFAU. We gratefully acknowledge financial support from U-CARE, the European Research Council (grant 683214 CONPOL), and FORTE (Dnr 2013-2482). This study has been approved by the Regional Ethical Review Board in Uppsala (Dnr 2015/530). This published paper is a heavily revised and shortened version of the working paper Aggeborn and Öhman (2017). Do-files and instructions for data access for replication purposes are provided as supplementary material online.

Electronically published January 13, 2021
[*Journal of Political Economy*, 2021, vol. 129, no. 2]

I. Introduction

It is well established that fluoride strengthens tooth enamel and that fluoride prevents caries, tooth decay, tooth loss, and cavities (e.g., Twetman et al. 2003; Neidell, Herzog, and Glied 2010; Medjedovic et al. 2015; O'Mullane et al. 2016). The use of fluoride in dental products is therefore viewed as an important mean to improve dental health. Furthermore, countries such as Brazil, Malaysia, the United Kingdom, and the United States artificially fluoridate drinking water for public health reasons so that people are continuously exposed (Mullen 2005). The Centers for Disease Control and Prevention (CDC 1999) considers water fluoridation as one of the ten great public health achievements during the 20th century.

However, several epidemiological studies in recent years have found negative associations between fluoride and cognitive development. Bashash et al. (2017) concluded that children in Mexico had a lower intelligence quotient (IQ) if their mothers consumed more fluoride during pregnancy. Green et al. (2019) reached a similar conclusion in their study on Canadian children if the mothers drank fluoridated water. An increase of 1 milligram of fluoride was associated with a decrease of almost 4 IQ points, where the overall association was driven by boys. These results have intensified the debate among scholars regarding whether fluoride is neurotoxic (see Bellinger 2019). After the publication of Green et al. (2019), the American Dental Association released a statement in which they welcome more studies on the issue (ADA 2019). These findings echo earlier results of a negative association between fluoride and IQ. A metastudy by Choi et al. (2012), based on data from China and Iran, concluded that exposure to high doses of fluoride in water was associated with a reduction of almost a half a standard deviation in IQ among children. Many of the reviewed papers considered levels that surpass the recommendation from the World Health Organization that fluoride should not exceed 1.5 milligrams/liter in drinking water (WHO 2011, 42). However, some of the reviewed studies reported negative associations with cognitive development for levels below the recommended level. This motivates more research, given that these levels are present naturally or artificially in drinking water in many parts of the world. Common problems with the studies reviewed in Choi et al. (2012) are that they were based on smaller data samples with potentially low data quality.[1]

[1] The US Public Health Service (2015) acknowledges the potential methodological obstacles of the reviewed studies in Choi et al. (2012). It is worth noting that several of the reviewed papers were not published in English. More recent papers, which may be argued have similar problems, have been published after 2012. Interestingly, almost all studies, which originate from several countries, have found a negative association between fluoride and IQ: Ding et al. (2011), Saxena, Sahay, and Goel (2012), Seraj et al. (2012), Nagarajappa et al. (2013), Choi et al. (2015), Khan et al. (2015), Kundu et al. (2015), Sebastian and Sunitha (2015), Aravind et al. (2016), Das and Mondal (2016), Mondal, Dutta, and Gupta

Fluoride is known to be lethal in higher doses (Liteplo et al. 2002, 100), and intake of fluoride from water is absorbed and transmitted throughout the blood system (Fawell et al. 2006, 29–30). Furthermore, the negative link between fluoride and cognitive development has grounds in the experimental medical literature. Mullenix et al. (1995) conducted one of the first studies testing the hypothesis that fluoride has effects on the central nervous system. The researchers exposed rats to fluoride, including fluoridation of drinking water, and found that brain tissue stores fluoride and that it passes the blood-brain barrier. Higher concentrations in the brain induced behavioral changes, indicating that fluoride may function as a neurotoxin. The negative link between fluoride and cognition among rats has also been demonstrated in Liu et al. (2014). The question remains whether fluoride levels lower than those in the experiments may have a negative impact on humans when exposed for a longer time.

In light of these findings and the ongoing discussion among scholars, we study the long-term causal effects of fluoride in drinking water on cognitive ability. Our data originate from Sweden, where we have access to high-quality registry data. We exploit the fact that natural fluoride varies exogenously because of local geological characteristics at water sources. In addition to cognitive ability, we study the effects of fluoride on annual labor market income and dental health (and several related outcomes in the appendix, available online). Our paper focuses on the causal effects of fluoride in a large-scale setup with plausible exogenous variation in fluoride exposure. Sweden does not fluoridate water, but there is no evidence of differences between artificially fluoridated water and water with a natural occurrence of fluoride (John 2002; Harrison 2005; CDC 2014). Thus, our results have broad policy relevance. Sweden has a well-supervised water supply system, meaning that other drinking water hazards are not likely to be present. We argue that our empirical strategy and our data have advantages when studying the long-term effects of fluoride, and we therefore add to the epidemiological literature discussed above.

The effects of fluoride are of interest for two reasons. First, fluoridation of drinking water is a common public health program, and its effectiveness is important to evaluate. Given that fluoride is harmful in higher doses but improves dental health in lower ones, there is a trade-off. The optimal fluoride policy is where the marginal cost equals the marginal benefit; thus, for example, if the positive effect on dental health is large with only a small negative effect on cognitive ability, the net in a cost-benefit analysis could be positive in favor of fluoridation or in terms of not reducing the natural levels of fluoride.

(2016), Sharma et al. (2016), Jiménez et al. (2017), Razdan et al. (2017), Yu et al. (2018), Till et al. (2020), and Wang et al. (2020). Broadbent et al. (2015) and Barberio et al. (2017), however, found no negative association with IQ or learning disabilities from living in areas with artificial fluoridation.

Second, to an increasing degree, economists have modeled and empirically investigated determinants of human capital development. The model by Cunha and Heckman (2007) focuses on the accumulation of cognitive and noncognitive abilities, and Cunha and Heckman (2009) emphasize that there are critical and sensitive windows when these abilities are more affected by environmental factors. Cunha, Heckman, and Schennach (2010) conclude that interventions early in life are more effective than later ones. Childhood health has been linked to adult educational attainment and income (Case, Lubotsky, and Paxson 2002; Currie 2009; Almond and Currie 2011), and earlier studies have shown that cognitive ability is a reliable predictor for labor market status (e.g., Heckman, Stixrud, and Urzua 2006; Lindqvist and Vestman 2011). Thus, if fluoride has negative effects on cognitive development, it is an important environmental factor to consider when discussing human capital development.

There are some earlier studies by economists that have investigated hazards in drinking water.[2] Glied and Neidell (2010) found that women living in areas with fluoridated water in the United States had higher incomes and that this effect was stronger among those with a low socioeconomic background. Our paper adds to this literature as well as the general economic literature on human capital development.

II. Identification Strategy

The purpose of this paper is to estimate the long-term causal effects of fluoride exposure from drinking water. In this section we present our identification strategy, which is further elaborated in section B1 in the appendix.

The ideal empirical strategy would be to run a controlled experiment where fluoride is randomized on the individual level. However, it is obviously not feasible to randomly assign fluoride water intake from birth in a large-scale long-term setup. We argue instead that we can exploit a natural experiment.

The natural level of fluoride depends on local geological characteristics (SGU 2013, 81). Water sources are situated on different types of

[2] Galiani, Gertler, and Schargrodsky (2005) investigated water supply privatization in Argentina and found that child mortality decreased if an area had privately provided water. Zhang (2012) found that providing safe monitored drinking water increased the ratio of weight and height among adults and children and also found some evidence of less illness among adults when using water data from China. Ferrie, Rolf, and Troesken (2012) concluded that test scores from enlistment during World War II decreased by one-third of a standard deviation of the conscript if living in an area with lead water pipes in 1930. Currie et al. (2013) concluded that birth weight was negatively affected if mothers had consumed polluted drinking water during pregnancy, especially mothers with low education. Alsan and Goldin (2019) found that child mortality in Boston decreased when the city was provided with clean water and sewage systems around 1900.

bedrock, which yield different natural fluoride levels. Soil bedrock, for example, is associated with lower fluoride in comparison to granite bedrock (SGU 2013, 81, 84). Local veins of minerals and when water has been in contact with acidic igneous rocks especially increase the fluoride level (Edmunds and Smedley 2013, 314). Berger et al. (2016) found large spatial variation in the natural fluoride levels in groundwater within a small geographical area in Sweden, which suggests that fluoride may vary substantially depending on water source location. It is important to note that local geological characteristics at a water source do not necessarily map to the overall geology at the area of residence, given that drinking water is distributed to households by water treatment plants through water pipes managed by the municipalities. The large majority of Swedes drink municipality-provided water.[3]

Publicly provided drinking water in Sweden is monitored and purified according to regulations from the Swedish Food Agency (Livsmedelsverket 2001). The overall composition of drinking water is thus determined not only by local geological characteristics. One key element in our identification strategy is that water authorities normally do not consider fluoride levels of 0–1.5 milligrams/liter to be a problem, and they let the natural level remain during the water purification process. Many municipalities use several water sources, providing us with intramunicipality variation in fluoride due to different local geological characteristics underneath the water sources. The fluoride level is measured at the water treatment plants, and we map these levels to areas of residence on the small areas of market statistics (SAMS) district level. SAMS are nested within municipalities and include approximately 750 individuals in 2011. Additional information on the water data and the mapping are provided in section III.

In table 1, we demonstrate that the fluoride level is a function of the geological characteristics at the site of the water source, where we have grouped information on the bedrock for a subset in our water data. The bedrock is here classified into three categories: soil bedrock, mixed bedrock, and stone bedrock. The baseline in table 1 is soil bedrock, with dummy variables for the mixed and stone bedrock. Mixed bedrock and stone bedrock yield higher levels in comparison to soil bedrock, which is what we expect to find given the discussion above. These broader bedrock categories includes subtypes, meaning that there is variation in the fluoride within each category. Table 2 shows the variation in fluoride between and within the municipalities on the SAMS level. The levels range foremost between 0 and 1.5 milligrams/liter, with the maximum of 4.1 milligrams/liter.

[3] Some individuals have private wells for which we do not have data. Approximately 1.2 million people of Sweden's total population of approximately 10 million have private wells (Livsmedelsverket 2020).

TABLE 1
Water Source Bedrock Analysis

	F (.1 mg/L)
Mix stone/soil	2.983***
	(.526)
Stone	4.085***
	(.214)
Soil bedrock (constant)	3.057***
	(.129)
R^2	.1729
Observations	1,788

Note.—Standard errors are in parentheses. Observations are the number of water treatment plants in the entire SGU data set.
*** $p < .01$.

Fluoride is colorless, odorless, and tasteless for the levels we consider (WHO 2001), making self-selection into fluoride treatment unlikely. Given that there is variation in fluoride on the SAMS level within municipalities, we may control for unobservable characteristics at the municipal level. Since the geological characteristics at local water sources determine fluoride and not the overall geology at a larger area of residence, this means that fluoride is not part of a larger bundled geological treatment. Hence, we argue that the fluoride level is exogenous in relation to our outcomes and not endogenous to a policy choice for values below 1.5 milligrams/liter.

In addition to the spatial variation in fluoride, we exploit a second source of variation stemming from individuals' moving patterns. Moving is undoubtedly endogenous, but as long as the choice to move and the moving location are not dependent on fluoride or other variables correlated with fluoride, this yields an exogenous variation in the intensity of fluoride treatment, which depends on the number of years spent in a district. We show that the choice to move is not dependent on the fluoride level in table A1 (tables A1–A10, B1–B82 are available online).[4]

In conclusion, the natural experiment we exploit consists of determination of fluoride due to local geological characteristics at water sources in combination with moving patterns independent of the fluoride level. As a result, individuals will have an individual long-term fluoride treatment level in our data.

There are several potential threats to the identification strategy presented in this section. Section B1(a) in the appendix provides an extensive discussion on these threats. We address issues such as the problems of using geographical variation in the treatment variable (including bias because fluoride may be bundled with other characteristics), economic

[4] We also use data from Google Trends in table A2 and find no clear evidence that people overall search for more information about fluoride in areas where the fluoride level is higher.

TABLE 2
Decomposition of Fluoride Variation

	Mean	Standard Deviation
Fluoride (.1 mg/L)	3.53	
Overall		3.25
Between		2.95
Within		1.89
Observations	8,597	

Note.—Between and within variations are at the municipal level. Observations are the number of SAMS.

specialization as a result of the bedrock, sorting into neighborhoods, endogenous provision of drinking water by the municipalities, compensating behavior given that individuals may observe their dental history, and geographical clustering of individuals as a result of heritability. Balance tests related to this discussion are presented in sections B2(a)–B2(c) in the appendix. Our overall conclusion from this discussion and the results from the balance tests is that the identification strategy we use is valid. Next, we explain how we map fluoride levels to the SAMS districts.

III. Data and Mapping

Our main data on the individual level originate from Swedish population-wide registers for those born between 1985 and 1992, which we map to drinking water data. This section provides an overview of the data material, and we provide a more extensive presentation in section B3 in the appendix.

We take our starting point in tracking place of residence on the SAMS level between birth until the year when we measure the outcome in accordance with figure 1. For years under age 16, we use mothers' yearly SAMS of residence as a proxy, since we cannot observe yearly place of residence under age 16 in our data. We exclude all individuals who have ever lived in a municipality for which we do not have fluoride data between birth and age 16, and we exclude individuals who have immigrated during childhood, since we want to assign a fluoride treatment level from birth.

A. Fluoride Data

We have fluoride data on outgoing drinking water from 1,726 water treatment plants, which originate from two sources: Geological Survey of Sweden (SGU) and the municipalities. The first observation year in the SGU data is 1998, and we therefore contacted the water authorities at each municipality to complement the SGU data set to provide us with drinking water data from 1985 (the birth year of the first cohort). In all, we have data for 261 out of 290 municipalities, but we do not have a full panel for all

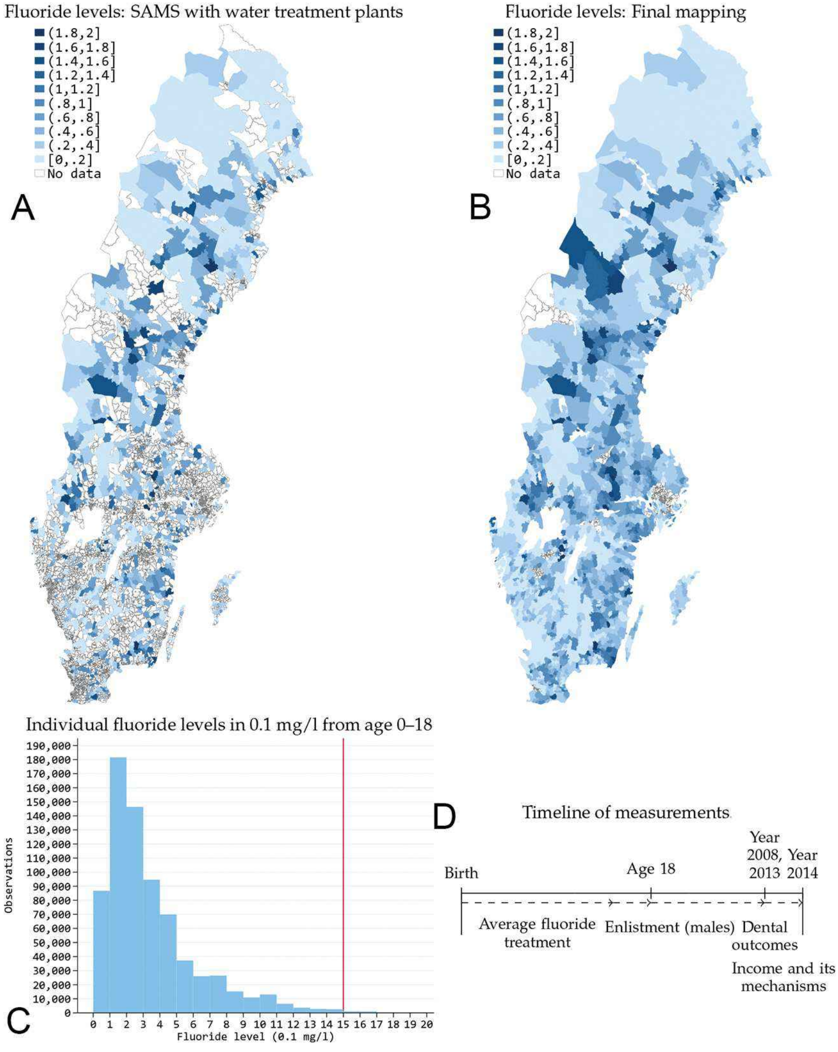

FIG. 1.—Fluoride mapping, individual treatment levels, and timeline of outcomes.

water treatment plants and years. However, variation between the years and back in time is foremost due to measurement precision, and because local geological characteristics at water sources change slowly, we collapse the fluoride level into an average measure for each water treatment plant in the main analysis. In a robustness analysis, we make use of the available time variation in fluoride.

We do not have data on the exact location of the water treatment plants, but we do have information on their names and the municipality to which they belong. Therefore, we have designated a proxy coordinate manually for each water treatment plant based on this information. Given that we observe place of residence for the individuals on the SAMS level, we map fluoride to entire SAMS districts. We have applied the following mapping protocol: if there is a single water treatment plant within the SAMS border, we assign the fluoride level of that water treatment plant to the entire SAMS (14% of all SAMS). If there are more than one water treatment plant, we take the average fluoride level (3% of all SAMS). If there are no water treatment plants within the border, we take a weighted average for the three closest water treatment plants within the municipality using the inverse distance to the center point of the SAMS as weight (84% of all SAMS). Figure 1 displays the fluoride levels for all SAMS districts before and after our mapping strategy was employed.[5] Together, this means that we have classical measurement error in our fluoride variable. We assess the mapping strategy by first investigating the effect of fluoride on dental outcomes for which we have a strong prior to find a positive effect of fluoride. This also investigate whether the variation in the fluoride treatment variable is sufficient for estimating any effects on other outcomes.

Individuals are assigned a fluoride level for each year, which depends on their yearly SAMS of residence, and we collapse this over-life exposure into a single treatment level from birth up until the year when we measure the outcome variable. The individual treatment level is thus an average, depending on the number of years within the specific SAMS districts. Figure 1 includes a histogram of the frequency of individuals who are treated with the corresponding level of fluoride. The level displayed in the histogram is the individual treatment level, taking into account moving patterns between different SAMS over time. As can be seen in figure 1, the overwhelming majority of individuals are treated with fluoride levels below 1.5 milligrams/liter.

B. Dental Health Data

The dental health data are aggregated on the SAMS level for each cohort for the years 2008 and 2013 and originate from the National Board of Health and Welfare in Sweden. In the main text, we focus on two categories of variables. The first category measures medical examinations and includes visits to dental health clinics, dental risk evaluation, and disease prevention measures. The second category includes variables measuring treatments, such as general treatment, dental repair, and root canal.[6]

[5] Some municipalities do not have a water treatment plant within their borders, and these have thus been dropped. This includes municipalities in the county of Stockholm.

[6] We also have access to other dental health outcomes. These variables are presented in table A3.

C. *Cognitive Ability and Annual Labor Income*

The cognitive ability measure originates from the Swedish military conscription. Conscription was mandatory for men ages 18–20 years in Sweden. Cognitive ability was measured by a test where the purpose was to measure the underlying intelligence, which we have standardized to mean 0 with a standard deviation of 1 for each cohort. We include only men born between 1985 and 1987 when estimating this outcome, since we have access to data for only those years. In order to broaden our analysis on cognitive development, we also study noncognitive ability, results from a national math test taken in ninth grade, and health outcomes (psychiatric and neurological diseases) in the appendix.

Regarding income, we have gross annual labor income measured in 2014 for those born between 1985 and 1992. The data originate from Statistics Sweden. We exclude all individuals who earned less than 1,000 Swedish kronor (about $110 in 2020) during a year. The reason is that we want to focus on those who have worked, but we also study employment status in the appendix.

IV. Econometric Setup

Cognitive ability and annual labor income are our main outcomes, whereas dental health outcomes are aggregated and used to investigate the first stage and to assess our mapping strategy.

In the empirical analysis for cognitive ability and labor income, we run regressions for both unconditional models and specifications where we include fixed effects and covariates. We include fixed effects for birth municipality, since there are differences between municipalities that might be determinants for our outcomes. To control for age, we include cohort fixed effects. We add municipality fixed effects for place of residence in 2014 when we measure labor income, since the income opportunities differ throughout Sweden. We add individual covariates (gender and marital status), parental covariates (income, years of education, and ability measures for fathers), and peer covariates (years of education in adulthood for those born in the same SAMS in a given year). The covariates and descriptive statistics are presented in table A4.[7]

[7] Most SAMS do not have a water treatment plant within the borders, meaning that the fluoride level is not independent of the other SAMS within the same municipality, given our mapping strategy. Therefore, we cluster standard errors by municipality of birth. This is the benchmark level that we use throughout the paper. In the main analysis, we also estimate standard errors clustered by SAMS. Moreover, we estimate spatial adjusted standard errors in line with Conley (2008) with the MATLAB code from Hsiang (2010), using 10 kilometers from the center point of the SAMS as a cutoff in the main analysis. In order to facilitate computation of the Conley standard errors, we have demeaned the data given that we have many fixed effects. Since we do not have a panel data set, we are not correcting

For dental health, there are different alternatives for the empirical setup, because dental health is not available on the individual level. In the main text, we present results from the simplest unweighted specification without fixed effects or covariates, where each observation is a cohort SAMS with a corresponding SAMS fluoride level for the youngest cohort available in our data. These 20-year-olds may visit the dentist for free, meaning that there are no monetary constraints. This cohort is also more likely to still reside in the SAMS area in which they have spent time during childhood, meaning that we capture a more long-term treatment effect. Section B4 in the appendix includes specifications for all cohorts and weighted regressions taking into account the number of individuals in each SAMS cohort, where each individual has a unique fluoride treatment but where the outcome is aggregated.

V. Results

We start this section by presenting the effect of fluoride on dental health and then present the results for our main outcomes, cognitive ability and annual labor income. Throughout this entire section, we are going to analyze an increase of 1 milligram/liter in fluoride, since this is the policy-relevant increase for countries considering fluoridation in water.

A. Dental Health

If our mapping strategy is adequate, we expect to find a positive effect of fluoride on dental health, which is what we find in table 3. An improvement in dental health corresponds to negative estimates for the outcomes given that we measure in dental health care consumption. Outcomes are expressed as shares in percentage points.

The results are negative and large across the board, with the exception of one coefficient (Disease Treatment 2008), and often statistically significant. The outcome that should be mostly related to fluoride is tooth repair, displayed in column 5. If fluoride increases to 1 milligram/liter, the share of 20-year-olds who had a tooth repaired decreases by 3.4 percentage points, considering the 2013 sample. On average, 20-year-olds have healthy teeth, but we still find effects from fluoride. The results both reconfirm the long-established positive effect of fluoride on dental health and provide credibility to the mapping of fluoride to the SAMS districts. Additional specifications are presented in section B4 in the appendix, which overall supports the findings presented here.

for temporal correlation. For annual labor income, we furthermore estimate standard errors clustered by local labor market region.

TABLE 3
Dental Outcomes

	Dependent Variable					
	Visit	Risk Evaluation	Disease Prevention	Disease Treatment	Repair	Root Canal
2013	−.6554	−.6882	−.8453	−.3506	−.3369	−.0292
	(.2987)**	(.3015)**	(.4309)*	(.1389)**	(.1103)***	(.0172)*
	<.0879>***	<.0906>***	<.0835>***	<.0757>***	<.0555>***	<.0156>*
2008	−.6356	−.6765	−.4337	.1093	−.2290	−.0300
	(.2935)**	(.3204)**	(.2238)*	(.1056)	(.0683)***	(.0197)
	<.0949>***	<.0974>***	<.0764>***	<.0646>*	<.0589>***	<.0168>*

Note.—Standard errors are clustered by municipality (in parentheses) and by SAMS (in angle brackets). There are 7,622 observations for 2013 and 7,606 for 2008. Fluoride (0.1 milligrams/liter) at the SAMS level is the independent variable.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

B. *Cognitive Ability and Annual Labor Income*

Let us continue to our main results. We begin with cognitive ability for men born between 1985 and 1987. Our conclusion from table 4 is that fluoride does not affect cognitive ability.

Column 1 displays the unconditional treatment effect. In columns 2 and 3, we add fixed effects for cohort and municipality of birth. We then include parental covariates, which results in a reduced sample since we have data on fathers' cognitive ability only from 1969 and onward. To make the samples comparable with and without these covariates, we run column 4 for the same sample as in column 5. We also run two subsample analyses: in column 6, we run the analysis for those who have lived in the same SAMS in a municipality for the entire period from age 0 to 18, and in column 7 we restrict the sample to those who have moved only within a municipality.[8]

Looking at the estimates, they are very small and often not statistically significantly different from zero. Sometimes the estimates are negative and sometimes positive, but they are always close to zero. If we take the largest negative point estimates (−0.0047, col. 1) and the largest standard error for that specification (0.0045), the 95% confidence interval would be −0.014 to 0.004. We may thus rule out negative effects larger than 0.14 standard deviations in cognitive ability if fluoride is increased by 1 milligram/liter (the level often considered when artificially fluoridating the water).

8 We have tested whether the estimated coefficients in cols. 5–7 are statistically different from each other using clustering by municipality of birth. The coefficients in cols. 6 and 7 are not statistically different from each other, and neither are the coefficients in cols. 5 and 6. The estimates in cols. 5 and 7 are statistically different at the 10% level.

TABLE 4
Cognitive Ability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fluoride (age 18)	−.0047	−.0015	−.0015	−.0001	.0028	.0031	.0099
	(.0043)	(.0027)	(.0026)	(.0029)	(.0023)	(.0032)	(.0045)**
	<.0016>***	<.0020>	<.0020>	<.0024>	<.0022>	<.0031>	<.0047>**
	{.0045}	{.0024}	{.0024}	{.0028}	{.0023}	{.0031}	{.0048}**
Mean	.0015	.0015	.0015	.0233	.0233	.0531	−.0252
Birth cohort fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Municipality of birth fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariate group 2	No	No	No	No	Yes	Yes	Yes
Sample	All	All	All	Column 5	All	Stayers	Movers
R^2	.0002	.0216	.0216	.0262	.1512	.1530	.1565
Observations	81,776	81,776	81,776	47,242	47,242	18,894	17,865

Note.—Fluoride concentration is 0.1 milligrams/liter. Standard errors are clustered by municipality of birth (in parentheses) and by SAMS of birth (in angle brackets). Conley standard errors (in curly brackets) have a cutoff of 10 kilometers, centered on each SAMS.
** $p < .05$.
*** $p < .01$.

However, the effect of fluoride may not be linear. We have therefore run several specifications addressing nonlinearities, and the results are presented in the appendix. Figure A1 displays the effect for each 0.1 milligram/liter of fluoride, table A5 present results for quartile regressions, table A6 is a dose response analysis, and table A7 is an analysis where we have restricted the sample to 1 milligram/liter or higher. Figure A2 is a spline regression where we have predicted cognitive ability on a set of background characteristics. We then use the ranked predicted values to run regressions with fluoride as the independent variable in a flexible interaction model, where fluoride is interacted with a vector of cubic splines. The spline specification picks up nonlinear treatment heterogeneity over the predicted cognitive ability distribution. All in all, we conclude that fluoride does not have an effect on cognitive ability in these nonlinear specifications.

We have furthermore run analyses for noncognitive ability, math test scores, and health, which are presented in section B5 in the appendix. This analysis further strengthens our conclusion that fluoride does not have a negative impact on human capital development.[9]

[9] For math test score, we estimate negative and statistically significant coefficients. However, the magnitude of these coefficients are very small, and we judge them to be zero effects in terms of economic significance.

We now continue with the long-term outcome of annual labor income in 2014 for individuals born between 1985 and 1992. Given our results for cognitive ability, we do not expect negative effects of fluoride. However, positive effects are possible given the results found for dental health.

The results are presented in table 5. The point estimates are often statistically significant, and the coefficients are always positive. Taking column 6 as an example, where all covariates and fixed effects are included, we find that the point estimate equals 0.0044, meaning that income increases by 4.4% if fluoride is increased by 1 milligram/liter.[10] These reduced form estimates may be compared with Glied and Neidell (2010), who, by using American data, found that women who drink fluoridated water have on average 4% higher earnings.[11] Our estimated effect on income may also be compared with estimated education premiums. The return of one additional year of education yields an increase in income by 6%–10%, according to the instrumental variable estimates in the review in Card (1999). An increase in fluoride by 1 milligram/liter would thus yield a similar increase as roughly half a year of additional education. Nonlinear specifications are presented in figure A1 (figs. A1–A5, B1–B14 are available online) and tables A8–A10, which overall supports the findings presented here. In section B5 in the appendix, we present the result for employment status (another margin for labor market status), and we find that fluoride has a positive effect.

We have run several robustness checks for our main outcomes, which are presented and discussed in section B6 in the appendix. These include (1) analyses with older cohorts for income, (2) sensitivity tests to the mapping of the water data, (3) alternative income measures, (4) included interacted fixed effects, (5) an intention-to-treat model, (6) analyses using time variation in fluoride, (7) in utero treatment effects, (8) secondary dentition treatment analyses, (9) analyses including SAMS covariates, (10) specifications for various forms of family robustness, and (11) analyses including covariates for other water characteristics. All in all, after considering these robustness results, we remain with our conclusions presented here that fluoride improves dental health, that fluoride does not affect cognitive ability, and that fluoride has a positive effect on annual labor income. These robustness checks are numerous, and most of them are in line with the results presented here, but some specifications do not go in the expected direction. For a more detailed discussion, see the appendix.

[10] No pairwise comparison test between coefficients in cols. 6–8 are statistically significantly different from each other (clustering by municipality).

[11] Glied and Neidell (2010) use Armed Forces Qualification Test scores in a falsification test to assess the exogeneity of their water fluoridation measure for a sample in their data. They estimate a small negative but statistically insignificant coefficient when considering both males and females. This is not further developed in Glied and Neidell (2010).

TABLE 5

Log Annual Labor Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fluoride (2014)	.0053	.0035	.0040	.0053	.0041	.0044	.0034	.0015
	(.0031)*	(.0014)**	(.0014)***	(.0016)***	(.0015)***	(.0015)***	(.0024)	(.0044)
	[.0023]**	[.0026]	[.0028]	[.0015]***	[.0018]**	[.0019]**	[.0022]	[.0041]
	<.0007>***	<.0008>***	<.0008>***	<.0008>***	<.0010>***	<.0010>***	<.0010>***	<.0010>***
	{.0031}*	{.0010}***	{.0011}***	{.0012}***	{.0013}***	{.0013}***	{.0021}	{.0027}
Mean	11.9124	11.9124	11.9124	11.9124	11.9237	11.9237	11.8415	11.9555
Birth cohort fixed effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Municipality of birth fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality fixed effects (2014)	No	No	No	Yes	Yes	Yes	Yes	Yes
Covariate group 1	No	No	No	Yes	Yes	Yes	Yes	Yes
Covariate group 2	No	No	No	No	No	Yes	Yes	Yes
Sample	All	All	All	All	Column 6	All	Stayers	Movers
R^2	.0002	.0065	.0528	.0936	.0985	.1044	.1261	.1170
Observations	634,793	634,793	634,793	634,793	390,226	390,226	67,457	140,666

Note.—Fluoride concentration is 0.1 milligrams/liter. The outcome is measured as log annual income in Swedish kronor (SEK). Individuals with a yearly income below 1,000 SEK are excluded. Standard errors are clustered by municipality of birth (in parentheses), by local labor market area (in square brackets), and by SAMS of birth (in angle brackets). Conley standard errors (in curly brackets) have a cutoff of 10 kilometers, centered on each SAMS.

* $p < .10$.

** $p < .05$.

*** $p < .01$.

C. *Disentangling the Effect on Annual Labor Income*

To disentangle the positive effect on annual labor income, we first investigate heterogeneous treatment effects for socioeconomic status and, second, potential mechanisms that could explain our reduced form finding. Additional results are found in section B7 in the appendix.

To capture socioeconomic status, we run the same nonlinear analysis as we did when analyzing cognitive ability (fig. A2), where we predict individual income on a set of background characteristics. The distribution of predicted values is displayed in figure 2*A*.[12] The marginal effect of an extra 0.1 milligram/liter of fluoride on log annual labor income is plotted in figure 2*B*. We find that the positive effect is driven by individuals with a low socioeconomic background. This points us toward the conclusion that fluoride treatment has an equalizing effect in terms of income. Since the treatment is found to benefit those with a disadvantaged background, this collaborates with earlier findings regarding early interventions (Cunha et al. 2006).

Turning to the intermediate mechanisms, we hypothesize, on the basis of our earlier findings, that the effect of fluoride on labor income goes through dental health capital. The remaining question concerns the intermediate steps. Theoretically, in equilibrium, workers earn the same income if they and the firms they work at are assumed to be homogeneous, with free entry and exit in a competitive labor market. However, if workers and firms differ, this would result in differences in earned income. We illustrate potential channels for workers in figure 3.

Starting with workers' productivity, less dental pain should make an individual more productive. However, the impact of fluoride and, in turn, the impact of dental health on productivity could differ in terms of severity. If the impact is substantial, workers treated with fluoride could have a higher labor supply on the intensive margin, and earlier literature has highlighted that poor health reduces hours worked (Currie and Madrian 1999, 3319). In the main analysis, we study annual labor income, which roughly corresponds to wage times hours worked. Our first productivity channel focuses on hours worked as an intermediate step. We have data not on actual hours worked but on contracted hours for a representative sample.[13]

However, productivity can be affected in other less severe ways. Even if an individual does not reduce contracted hours worked on a more

[12] Birth year, gender, municipality of birth, and parental income, education, and immigration status are used to predict income. We use col. 1 specifications in table 5, given that covariates and fixed effects are used for the prediction.

[13] Data include all individuals working at public employers, all individuals working at private employers with over 500 employees, and a representative sample for smaller firms. We use survey weights in the regressions.

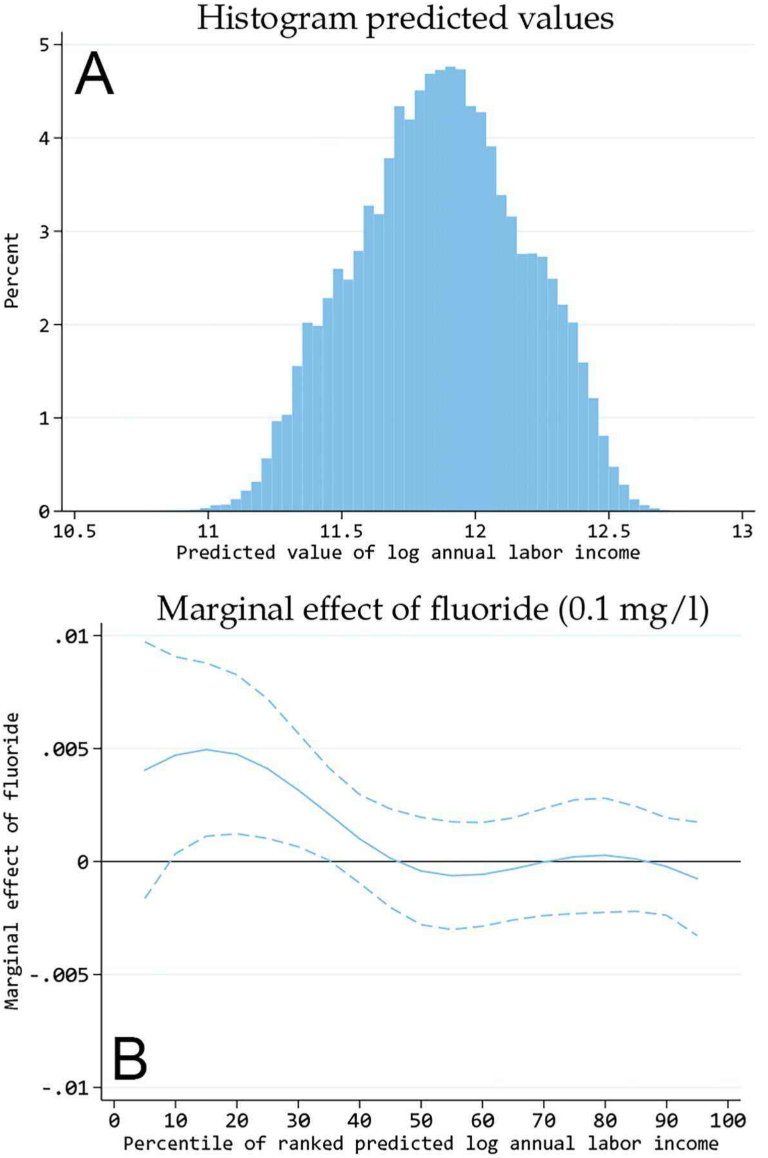

FIG. 2.—Effect of fluoride on log annual labor income by predicted socioeconomic status.

permanent basis, an individual may be less absent from work because of health problems if treated with fluoride. We measure this second channel by constructing a proxy for annual sickness benefits if the individual is absent from work for more than 14 days during a sickness spell. We focus on

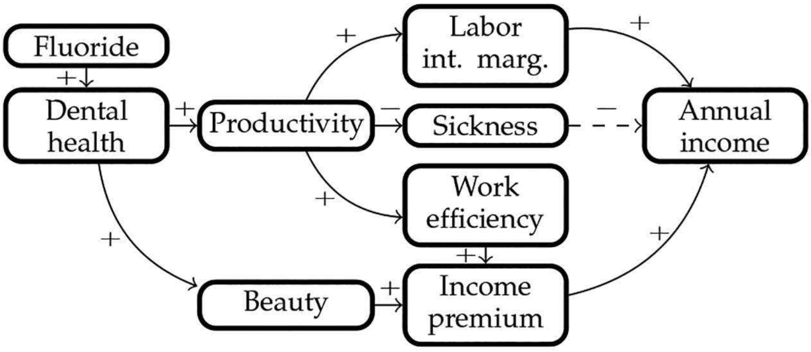

Fig. 3.—Mechanism channels.

workers with positive values for this variable, which we interpret as a proxy for absence from work for longer periods.[14]

The third channel captures an even less severe impact on workers' productivity. In this case, the effect of fluoride on labor income is not due to contracted hours worked or sickness absence longer than 14 days but is instead due to worker output. For example, a worker could be more efficient at work if treated with fluoride (and, as a result, have better dental health). We cannot observe individual output, but we observe place of work, type of profession, and other worker characteristics, meaning that we can observe income differences for workers that are very similar. Ceteris paribus, these workers should earn similar incomes if being equally productive. This analysis further relates to firm differences. By investigating within-workplace effects of fluoride, we purge our reduced form effect in table 5 from firm compensating differentials.

In table 6, we focus on the two more severe productivity channels. We first display the association between the intermediate variables and annual labor income. As expected, an increase in contracted hours is associated with higher annual labor income, and more sickness benefits are associated with lower annual labor income. We then investigate how fluoride affects these intermediate variables. We find that contracted hours worked are not affected. If fluoride is increased by 1 milligram/liter, the hours worked share (expressed as share of full employment, 0%–100%) is decreased by 0.3 percentage points (equal to a 7-minute reduction in a 40-hour work week), and the coefficient is not statistically significant. However, we find that the sickness benefits for spells longer than 14 days are reduced by 6% if fluoride is increased by 1 milligram/liter, which may indicate that

[14] We do not have data on sickness benefits, so we use a modified version of the variable social income from Statistics Sweden. See sec. B3 in the appendix for more information on how this variable is constructed.

TABLE 6
LABOR-INTENSIVE MARGIN AND LOG SICKNESS PROXY AS MECHANISMS

	Labor Intensive	Sickness
Annual labor income (dependent)	.010	−.279
	(.000)***	(.003)***
Fluoride (.1 mg/L; independent)	−.027	−.006
	(.081)	(.002)**
Observations	246,411	95,598

NOTE.—Standard errors (in parentheses) are clustered by municipality of birth. Specification is col. 4 in table 5. Dependent and independent refer to the dependent and independent variable in the regression.
** $p < .05$.
*** $p < .01$.

workers have fewer absences. However, one should note that only one out of six individuals in the sample in table 5 have received such benefits. In section B7 in the appendix, we further demonstrate that the result for this intermediate step is driven by those with high predicted sickness benefits. One explanation is that these people, in general, have poor health, which is linked to dental health (Petersen 2003). Because of fluoride, they at least have better dental health, reducing their absences. However, it is unlikely that this could explain the overall effect on labor income.[15]

We therefore turn to the third and least severe productivity channel. In column 1 in table 7, we compare log annual labor income for individuals who work in the same municipality and the same sector (narrowly defined using the five-digit code from the Swedish Standard Industrial Classification [SNI]) and are of the same cohort group. The individuals are grouped in 2-year cohorts to gain power. Although it is likely that some of these individuals work at the same workplace, we cannot know this with certainty. For columns 2–6, therefore, we focus on actual workplace indicators, but these data are available only for the same representative sample as used when investigating contracted hours worked. In column 2, we compare workers in the same workplace. In column 3, we further restrict the group of workers to the same occupation group (one-digit code from the International Standard Classification of Occupations [SSYK]). We add cohort group as a restriction in column 4 and gender in column 5. Column 6 is the same as column 5 but for workplaces with fewer than 20 employees among those in our sample.[16]

[15] The results for this mechanism channel are also sensitive to the model specification. See sec. B7 in the appendix for more details and additional results.

[16] The reason for not including fixed effects or additional covariates for municipality at birth and municipality of residence in 2014 is that the included interacted fixed effects capture almost all of the relevant between-individual variation, which the high R^2 indicates. Robustness analysis for this mechanism analysis is found in sec. B7 in the appendix. Here we present results for using two-, three-, and four-digit SSYK codes, and the results are similar to the ones presented here in the main text, although less precisely estimated.

TABLE 7
WITHIN-WORKPLACE EFFECTS ON LOG ANNUAL LABOR INCOME

	(1)	(2)	(3)	(4)	(5)	(6)
Fluoride (2014)	.00522**	.00376**	.00362**	.00396*	.00435*	.00620
	(.00216)	(.00171)	(.00162)	(.00217)	(.00244)	(.00669)
Fixed effects	Municipality × sector × cohort group	Workplace	Workplace × occupation	Workplace × occupation × cohort group	Workplace × occupation × cohort group × gender	Workplace × occupation × cohort group × gender
Workplace sample		All	All	All	All	WP < 20
R^2	.3533	.4161	.5224	.6640	.7097	.8570
Observations	626,113	228,313	222,712	222,712	222,712	122,427

NOTE.—Fluoride concentration is 0.1 milligrams/liter. Standard errors (in parentheses) are clustered by municipality of birth. Column 1 is based on the data set used in table 5, where the main effects for income are presented. Columns 2–6 are based on a representative sample including all public employees and a sample of private employees. Survey weights are therefore included. In col. 6, we restrict the employees to fewer than 20 individuals within our sample (WP < 20).

* $p < .10$.
** $p < .05$.

From table 7, we draw two conclusions. First, the estimated effect of fluoride on annual labor income in table 5 is similar when restricting the analysis to similar workers within the same workplace. This means that sorting and firm differentials cannot explain the overall reduced form effect on labor income. Instead, a likely explanation is differences in workers' human capital and productivity within workplaces. Second, the within-workplace effect on income is larger when considering smaller workplaces (col. 6), although the estimated coefficient is no longer statistically significant. One explanation may be that it is easier to monitor relative productivity differences in smaller firms. The exact mechanism at play depends on the firm, but one explanation would be related to a tournament wage schedule, where relative individual productivity within firms determines wages (e.g., Lazear and Rosen 1981) under the assumption that firms more easily observe relative rather than absolute productivity differences.[17]

Let us take this within-workplace analysis one step further. Are the results in table 7 driven by specific sectors in the labor market, or is it a general result? Figure A3 shows no indication of differences in average individual fluoride treatment between sectors. In figure A5, we run the same analysis corresponding to column 2 in table 7 but for the 66 labor market sectors represented in our data, defined by two-digit sector codes (SNI). Given that we now split the within-workplace analysis into sectors, some groups will include only a few individuals, meaning that the estimates become imprecise.

From figure A5, we may draw two conclusions. The within-workplace income premiums are found for many sectors in the labor market. This would be in line with an explanation where individuals become more efficient at work in general. Interestingly, the effect seems to be relatively large in sectors in which workers have customer contact, where good-looking teeth and good breath is important. This hypothesis originates from Blinder (1974), who provides an early analysis on teeth and income. The sectors where the within-workplace effect of fluoride is above the average effect includes, among others, hair dressers and beauty consultants, travel agents, creative arts and entertainment workers, and those working at hotels and those working with sales but also, for example, those working in manufacturing, hunting, and land transport.[18] We do not want to stress these results

[17] In the appendix, we have also run an analysis for monthly wages. Monthly wages are positively affected by fluoride but to a smaller degree than income, and the coefficients are not statistically significant for all specifications. This could indicate that a part of the effect of income is due to a wage premium for being more productive while at work and a part of being more productive in terms of being present at work. Sickness spells shorter than 14 days are paid out by the employer and hence part of the income measure. However, the reimbursement is not 100% of the wage, meaning that sickness spells decrease annual income.

[18] The results are sensitive on how survey weights are applied. Additional results are presented in sec. B7 in the appendix.

too far given their exploratory nature, but they provide weak indirect evidence that beauty due to dental health may be one salient mechanism.

The overall conclusion from our mechanism analyses is that the effect of fluoride is first and foremost due to less severe productivity differences between workers. The previously estimated reduced form effect on labor income is reproduced when we run a within-workplace analysis comparing similar workers. Fluoride has been found to have a positive impact on dental health, which points us toward the conclusion that dental health capital makes individuals more productive, yielding higher labor incomes. In addition, we found indirect indications that this within-workplace income premium is relatively large in sectors where workers have customer contact. We also found that for a small group of workers with high predicted sickness benefits, their received benefits decreased when the individuals were treated with fluoride. We do not find fluoride to have such a profound impact on productivity that it affects contracted hours worked. One explanation is that the Swedish labor market is not flexible on the intensive margin.

VI. Discussion and Conclusion

Let us now return to our findings on cognitive ability. We claim that we find no effect of fluoride on cognitive ability, but is the estimated effect effectively zero? Let us monetize the estimates by relating them to earlier published findings on the predicted power of cognitive ability. We then choose column 5 in table 4, where fixed effects and covariates are included. Our point estimate is 0.0028, with fixed effects and covariates included, for an increase of 0.1 milligrams/liter of fluoride on cognitive ability.

Lindqvist and Vestman (2011) estimate the return of cognitive ability on wages using Swedish registry data. Let us do a back-of-the-envelope calculation. Their results in table 1 indicate that a 1 standard deviation increase in cognitive ability yields an approximately 10.4% increase in wages. We multiply their return to cognitive ability with our results for the effect of fluoride on cognitive ability. The estimated effect of an increase of 1 milligram/liter of fluoride translates to an 0.29% increase in wages.[19] In conclusion, the close to zero and insignificant result that we estimate for the effect of fluoride on cognitive ability translates to a small impact on wages.

Another way to evaluate a zero result is to look at earlier studies that have found statistically significant results and compare the precision of the estimates. Our study includes more than 80,000 individuals when we do not include covariates or fixed effects and about 47,000 individuals

[19] This may be compared with our reduced form results of fluoride on income in table 5 (note that this is not exactly the equivalence of wages), which is much larger.

with covariates and fixed effects. This may be compared with Green et al. (2019), which included around 600 observations, and the reviewed studies in Choi et al. (2012), where the number of observations was less than 1,000 for the largest study. Our confidence intervals are tighter than the 95% confidence intervals in all earlier studies.[20]

The remaining question is why our results deviate from previous studies, such as Green et al. (2019), that have considered similar fluoride levels.[21] The main objection against Green et al. (2019) is that the choice of fluoridating water is an endogenous policy variable. Individuals do not exogenously live in fluoridated areas, making it likely that there are selection problems present. It is also noteworthy that Green et al. (2019) find a negative association only for boys and not for girls. However, we should note that Green et al. (2019) have access to urine data with actual fluoride measures within the body and several background variables that we do not have access to and that they also measured IQ at a younger age than we do.

Our results are policy relevant for developed countries with water fluoridation, given that water authorities seldom consider fluoridation above 1.5 milligrams/liter. How do our results relate to developing countries in terms of external validity? We have no reason to expect that the effect of fluoride on cognitive ability is dependent on the institutional setting. Fluoride is a chemical substance, and its effect on cognitive development should not be specific to Sweden. Choi et al. (2012) consider studies from China and Iran with fluoride levels similar to ours but also studies with higher levels, and they concluded an overall negative association. Although the mass of fluoride is within the range of 0–1.5 milligrams/liter in our data, we have some observations above the 1.5 milligrams/liter threshold set by the World Health Organization. The share of observations in this upper limit is still large in comparison to the studies reviewed in Choi et al. (2012). Figure A4 and table A7 focus on these high-level treatment effects and display no evidence of a negative effect of fluoride up to at least 3 milligrams/liter. These results should be interpreted with caution given that it is a selected sample, but it covers many of the papers in Choi et al. (2012) in terms of range. Given that our results deviate from studies reviewed in Choi et al. (2012), we believe that many of the studies capture other simultaneous hazardous treatments.

Our paper is about not only cognitive ability but also the effect of fluoride on dental health and income. Regarding dental health, we believe

[20] Broadbent et al. (2015) also concluded a zero finding, but their confidence intervals are much broader than ours.

[21] Bashash et al. (2017) is also related, but they have fluoride from urine samples and not water data. One objection against this study is that fluoride intake is likely to be endogenous. For example, Bashash et al. (2017) writes that salt is fluoridated in Mexico, and the intake of salt is likely to differ between groups.

that our results are generalizable. Fluoride does improve dental health, and our natural experiment confirms this well-established finding in a long-term setting. However, we should remember that we measure dental health indirectly through the dental health care system in Sweden, with a large supply of dental care. The outcome where we expect to have the least external validity is our income measure, where the mechanism channels previously discussed are dependent on the institutional setting. It is interesting to note that our estimates on income, derived from rich and detailed population-wide data, are in line with Glied and Neidell (2010), who used American data.

Our findings add to the literature on the effects of fluoride on cognitive ability, but we have also broadened the understanding of the effects of fluoride by studying dental health (the first-stage relationship) and income (the long-term outcome). On the basis of the results, fluoride exposure through drinking water seems to be a good mean of improving dental health without negative effects on cognitive development for the fluoride levels considered in this study.

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