Cognitive Consequences of Iodine Deficiency in Adolescence: Evidence from Salt Iodization in Denmark

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Over the past three decades, many countries have introduced iodized salt policies to eradicate iodine deficiency. Iodine deficiency in utero is detrimental to cognitive ability, but little is known about the consequences of iodine deficiencies after birth. This paper examines the impact of iodine deficiency in adolescence on school performance. I exploit the introduction of iodized salt in Denmark during 1998-2001 as a natural experiment. Combining administrative records on high school grades over a thirty-year period with geographic variation in initial iodine deficiency, I find that salt iodization increases the GPA of students by 6-9 percent of a standard deviation.

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1 Introduction

More than two billion individuals lack essential vitamins and minerals (WHO et al., 2007), and these micronutrient deficiencies are major causes of disease globally. Over the past three decades, the WHO has initiated global efforts to increase food fortification, which has reduced the incidence of micronutrient deficiencies (Allen et al., 2006). The adoption of iodized salt to eradicate iodine deficiency is a leading example of such food fortification. Iodine is a crucial mineral for metabolic functioning and brain development. While iodized salt has been used since the 1920s in the US and Switzerland to prevent goiter, it became a global health policy after the 1980s, as researchers established that iodine deficiency during pregnancy is detrimental to brain development in children. In 1993, the WHO recommended worldwide adoption of iodized salt, and from 1990 to 2007 a large number of countries introduced salt iodization policies, thereby increasing worldwide access to iodized salt from 20 to 70 percent (WHO et al., 2007).

Today, iodine deficiency is recognized as the leading cause of preventable mental retardation (WHO et al., 2007) and recent studies in economics have shown that the introduction of iodized salt in the US and Switzerland increased the average IQ, educational attainment and adult earnings of individuals exposed while in utero (Politi, 2010, 2015; Feyrer et al., 2017; Adhvaryu et al., 2020).

However, while salt iodization affects the entire population, little is known about the cognitive effects on individuals exposed after birth. A small experimental literature finds that iodine supplementation improves cognitive performance among school-age children (Zimmermann et al., 2006; Gordon et al., 2009), but it is unknown whether the benefits found in these small-scale controlled experiments also apply to real-world food fortification, and, in particular, to the recent wave of salt iodization policies implemented around the world.

This paper studies the contemporaneous effects of salt iodization on school performance. Specifically, I estimate the effect of the introduction of iodized salt in Denmark during the period 1998-2001 on the Grade Point Average (GPA) of high school students.

The Danish fortification policy provides unique conditions to study the effect of the recent wave of salt iodization policies. First, the policy was implemented within a few years and legislation changed from an implicit ban on iodized salt to mandated iodization of salt. Because of a conservative view on food fortification and a belief that iodine deficiency was not a concern in Denmark, the Danish National Food Agency did not allow the sale of iodized salt until 1998. After several studies confirmed that iodine deficiency was a concern in Denmark, legislation changed to voluntary iodization of salt in 1998 and mandated iodization of salt after 2001. This sharp policy change resulted in a large and immediate improvement in the iodine status of the population, providing an ideal experiment to study the effect of salt iodization.

Secondly, before the introduction of iodized salt the degree of iodine deficiency in Denmark varied substantially across areas due to differences in the concentration of iodine in drinking water. Drinking water accounted for 25 percent of the iodine intake in Denmark and the concentration of iodine in water varies more than 100-fold across areas (Pedersen et al., 1999). As salt iodization should only matter in deficient populations, I use this natural source of variation in pre-existing iodine deficiency as a measure of treatment intensity in a Difference-in-Differences design. Hence, I compare the impact of the introduction of iodized salt across individuals living in areas with high and low concentrations of iodine in drinking water.

Lastly, the availability of high-quality administrative data over three decades makes it possible to credibly estimate treatment effects. I measure school performance in adolescence using the final grade point average of high school students. The data covers all students graduating from 1980 to 2011, providing 19 pre-reform years to verify the common trend assumption of the Difference-in-Differences method and 10 post-reform years to study the benefits of salt iodization. I combine the administrative records with information on the iodine concentration in local drinking water, based on data from ground water samples collected by the Geological Survey of Denmark and Greenland (GEUS).[1,2]

My main finding is that salt iodization increases the final GPA of high school students by 0.06-0.09 standard deviations. The effect is immediate, with grades increasing from the first year of implementation, suggesting that salt iodization produces a contemporaneous improvement in cognitive performance among adolescents. To my knowledge, this is the first evidence that the benefits of salt iodization are not limited to the in utero period.

The estimated benefits of salt iodization are of the same order of magnitude as recent estimates of the effect of improved school lunch quality on students' test scores in US public schools (Anderson et al., 2018). Compared to more standard school achievement policies, the effect of salt iodization amounts to one-half to one-fourth of the benefit of reducing class sizes (Krueger, 2003). However, because salt iodization is very cheap, it is 20,000 times more cost-effective than reducing class sizes.[3] This suggests that even in developed countries, improving students' nutrition is a low-hanging fruit.

The results relate to a literature on the technology of skill formation (Cunha and Heckman, 2007). While the return to salt iodization in the prenatal period is, on average, larger, my results show that the return to investments in adolescence are non-neglible (Heller et al., 2017). I show that the benefits of salt iodization accrue to the lower end of the skill distribution with twice the increase in the bottom quartile of grades as in the top quartile of grades. This contrasts with the predictions of dynamic complementarities (Cunha and Heckman, 2007), in which returns increase with initial skills, and suggests that policies designed to correct nutritional deficiencies can reduce inequality in school performance (Deaton, 2003).

[1] GEUS is a research and advisory institution in the Danish Ministry of Energy, Utilities and Climate. Among other things, it collects and makes publicly available all water sample analyses used in the monitoring of drinking water quality. Additional information may be found at `https://eng.geus.dk/about/`.

[2] All drinking water in Denmark is derived from groundwater.

[3] According to estimates by the 2008 Copenhagen Consensus (Horton et al., 2008) the cost of salt iodization is 0.05 USD/person/year. Estimates of the costs and benefits of reducing class sizes comes from Krueger (2003). He estimates the cost of reducing class sizes from 22 to 15 students to be USD 3,385/student/year (1998 Dollars), see table 5, row 1 in Krueger (2003). The benefit from reducing class size is an increase in test scores of 0.2 standard deviations (Krueger, 2003).

Most studies of the benefits of salt iodization consider recent policies in poor countries (Field et al., 2009; Huang et al., 2020; Bengtsson et al., 2020) or historical policies in rich countries (Politi, 2010, 2015; Feyrer et al., 2017; Adhvaryu et al., 2020). I study a recent salt iodization policy in a wealthy country in Europe. Although iodine deficiency is not considered to be a public health concern in many European countries, Europe has the lowest rate of salt iodization of any WHO region (WHO 2007b) and 44 percent of school-age children in Europe do not consume adequate amounts of iodine (Andersson et al., 2012). Hence, my results suggest that even though severe iodine deficiency is rare in Europe, there are clear benefits to increasing access to iodized salt. To assess the postnatal benefits of salt iodization in more deficient countries, I estimate the relationship between initial iodine deficiency and the benefits of iodized salt and use this to extrapolate beyond the range of deficiency observed in Denmark. I predict an average treatment effect of 0.1 standard deviations for students with a moderate deficiency and 0.6 standard deviations for students with a severe deficiency. Globally, 8.1 percent of school-age children are moderately iodine deficient, while 5.2 percent are severely iodine deficient (Andersson et al., 2012). Hence, the benefits of salt iodization are potentially much larger in other countries.

My results confirm that the benefits of iodine supplementation to children found in experimental studies also apply to real-world fortification policies (Zimmermann et al., 2006; Gordon et al., 2009). However, the biological mechanism behind this result is unclear. Iodine deficiency may affect school performance in adolescence in two ways: (*i*) by impairing normal metabolic functioning, causing fatigue and reduced brain activity and (*ii*) by disturbing normal brain development during childhood and adolescence, causing permanent brain damage (Gordon et al., 2009). If salt iodization affects grades by preventing brain damage, the benefits should accumulate over time, resulting in larger treatment effects for students first exposed to iodized salt in early childhood versus late childhood. If salt iodization affects grades through the metabolism, only current iodine intake should matter and treatment effects should be identical for students first exposed to iodized salt in early or late childhood. Empirically, I find similar treatment effects for students first exposed to salt iodization at ages 6 to 18, i.e. between thirteen and one years before finishing high school. This suggests that in adolescence, iodine deficiency most likely affects school performance through its effect on the metabolism and not through brain damage. Since iodine deficiency affects the metabolism in all ages, this suggests that similar benefits may be found for adults. Considering that 29 percent of the world population and 30 percent of all school-age children remain mild to severely iodine deficient (Andersson et al., 2012), my results suggest that there is still a large untapped economic potential in scaling-up salt iodization.

The rest of the paper is structured as follows: Section 2 provides more background on the biology of iodine deficiency and outlines the Danish salt iodization policies. Section 3 describes the data. Section 4 explains the empirical method. Section 5 presents the main results. Section 6 evaluates the robustness and external validity of the estimates. Section 7 concludes.

2 Iodine Deficiency and Iodized Salt in Denmark

The adverse effects of iodine deficiency originate from disturbances to the production of thyroid hormones in the thyroid gland. Thyroid hormones regulate the metabolism of most cells of the body and a lack or excess of these is associated with a wide range of physical and psychological illnesses. When iodine intake is low, the body initiates a number of compensatory biological processes. The most important is thyroid enlargement, also known as goiter, which enables the thyroid gland to produce more thyroid hormones from a given input of iodine. While this compensation is effective when individuals are mildly iodine deficient, more severe cases result in insufficient thyroid hormone levels and a condition called hypothyroidism. Iodine-deficiency induced hypothyroidism may affect cognitive performance through two separate mechanisms.

The first mechanism pertain to the effects of hypothyroidism on the metabolism. With too low thyroid hormone levels the metabolism slows down. The symptoms include lethargy, weight gain, and impaired brain activity (Samuels, 2014). This condition may cause impaired cognitive performance in the short run, but is reversible through increased iodine intake.

The second mechanism pertain to the effects of hypothyroidism on brain development. Thyroid hormones control a wide range of processes responsible for the development of the brain and organs. During the prenatal period when brain development is most rapid (Gilmore et al., 2018), maternal hypothyroidism can cause irreversible brain damage and long-term consequences for cognitive ability of the child (Delange, 2001; Delange and Hetzel, 2004). While this second mechanism is especially important during the prenatal period, brain development continues throughout childhood and adolescence. Therefore, iodine deficiency in adolescence might cause irreversible brain damage and long-run consequences for cognitive ability.

While these two mechanisms hold different predictions, they could both be at play when considering the effects of salt iodization on adolescents. In the Results Section, I test and argue that the observed improvements in cognitive performance are consistent with the first mechanism going through the metabolism.

Excessive iodine consumption of up to 10 times the recommended intake is considered safe (Rasmussen et al., 1996). However, after long periods of iodine deficiency with overactivity and enlargement of the thyroid gland, the thyroid gland may be unable to return to normal activity (Laurberg et al., 2009). A subsequent increase in iodine intake, as with salt iodization, can lead to an excess production of thyroid hormones and a condition called hyperthyroidism. Hyperthyroidism is a known side effect of salt iodization. In contrast to hypothyroidism, hyperthyroidism is a state of overactive metabolism, causing nervousness, weight loss and sweating. Together with goiter, hypothyroidism and hyperthyroidism are the most common of iodine deficiency disorders.

2.1 Danish Salt Fortification

Salt iodization has been used to prevent high rates of goiter in the US and Switzerland since the 1920s. In Denmark, iodine deficiency was not considered a problem during most of the 20th century (Laurberg et al., 2009).[4] Several large studies of thousands of school-age children in

[4]This section is, to a large extent, based on a review article by Laurberg et al. (2009), which describes the historical context of the Danish fortification policy and the research of the DanThyr project - a research group set up to monitor the health effects of salt fortification in Denmark.

Denmark found up to 15 percent goiter rates in some groups of the population, but no indication of clinically relevant goiter on a national level. Therefore, the Danish National Food Agency declined applications from salt producers to add iodine to salt.[5] In the 1980s and 1990s evidence of iodine deficiency among older individuals and pregnant women started to accumulate, and in 1994 the Danish National Food Agency created a working group to determine whether an iodization program was needed. In 1996 the working group concluded that the population was mildly-to-moderately iodine deficient and that an iodized salt program should be implemented. In June 1998, the National Food Agency introduced a voluntary salt iodization program in collaboration with salt producers. The program was expected to increase the average daily iodine intake by 50 μg, from 50-100 μg/day (Rasmussen et al., 2002) to somewhere within the recommended range of 100-150 μg/day.

The voluntary program proved unsuccessful, with an average increase in iodine intake below 10 μg/day (Laurberg et al., 2009). Two years after implementation, only 50 percent of household salt and close to no salt in the food industry was iodized.[6] As a response, the National Food Agency decided to make the policy mandatory. This second reform was gradually implemented between July 2000 and April 2001, during which the remaining stocks of non-iodized salt could still be sold. According to estimates by Rasmussen et al. (2007), the two reforms combined met the goal of a 50 μg/day increase in average iodine intake. Both reforms were announced to the public and the issue received considerable media coverage in regional and national newspapers.

Even though the first and voluntary reform did not meet the target of a 50 μg/day increase in iodine intake, it might have caused a non-trivial reduction in thyroid hormone deficiency. Because the thyroid gland is partially able to compensate for iodine deficiency, the relationship

[5] Food producers have to apply for permission to sell fortified products.

[6] The voluntary policy failed in part because food producers were legally required to report that their products contained iodized salt, but were not allowed to explain why, to mention that it was recommended by the National Food Agency or to use it in advertisements. In contrast, salt producers were allowed to state that iodine was added upon the recommendation of the National Food Agency, which may explain why they complied with the voluntary policy. At the time of the reforms, the vast majority of household salt in Denmark came from Dansk Salt A/S, which introduced iodized salt, but did not discontinue selling non-iodized salt. Therefore, access to iodized salt was most likely equally-distributed throughout Denmark, while demand might have varied. While the voluntary policy in Denmark was not successful, voluntary salt iodization have been effective in many other countries, including in the US where salt producers were allowed to advertise for their fortified products.

between iodine intake and thyroid hormones is concave (Laurberg et al., 2010). Therefore, the small increase in iodine intake from the first reform might have been effective at alleviating the worst consequences of iodine deficiency, even though it did not eliminate iodine deficiency in Denmark.

The health effects of the Danish salt fortification policy have been studied extensively (see Laurberg et al. (2009) for a review). Using identification strategies similar to the one applied in this paper, medical researchers have confirmed that the increase in iodine intake following salt fortification led to a significant improvement in health, with a decrease in the incidence of thyroid enlargement from 17 percent before the reforms to 10 percent after (Vejbjerg et al., 2007). Medical researchers have also documented a temporary increase in the incidence of hyperthyroidism (Laurberg et al., 2009), consistent with a sudden increase in iodine intake after prolonged exposure to iodine deficiency. This suggests that the population was in fact iodine deficient prior to the reforms, and that the salt iodization policies were effective at increasing iodine intake. In Appendix Section A.1, I replicate these results using hyperthyroidism diagnoses at Danish hospitals. While hyperthyroidism is a temporary negative side effect of salt iodization, it is rare among the young and the observed increase in diagnoses is driven by the elderly.

3 Data

The empirical analysis is based on high quality Danish administrative data on school achievement. High school grades have been recorded since 1977, while the records for lower/middle secondary school grades only go back to 2002.[7] For this reason, I focus on high school students and their individual grade point averages as the main outcome of interest.

High school is voluntary in Denmark and students interested in upper secondary education can choose between four different programs that lead to the following final exams; (1) a standard Academic High School Examination (STX), (2) a Higher Technical Examination (HTX)

[7]In Denmark, school attendance is compulsory until the end of year 9. Children attend primary school ("Folkeskole") from kindergarten to year 9, which encompasses primary and lower/middle secondary education. High school refers to years 10 to 12.

focusing on science and technology, (3) a business-oriented Higher Commercial Examination (HHX), and (4) a Higher Preparatory Examination Course (HF) meant for adults interested in further education. STX, HTX and HHX are all three-year programs while HF is a two-year program.

Grades of HHX and HTX students are recorded from 1999 and are therefore not included in the analysis. As I consider the effect of iodine deficiency in adolescence and the HF program is intended for adults, HF students are also excluded. Hence, in the main analyses, I focus exclusively on STX students.

The STX program most closely resembles high school education in other countries and, over the data period, 60-70 percent of all high school students in Denmark were enrolled in the STX program. However, the main difference between the programs is the elective course catalog, and students can apply to all tertiary institutions, regardless of which high school program they graduate from. In the Appendix, I show that the main results are not sensitive to including HF students in the analysis.

Courses are categorized by A, B and C levels according to difficulty and duration. A-level courses are the most comprehensive and classes last from the first year of high school to graduation. C-level and B-level courses are predominantly one- and two-year courses, respectively. Grades take two forms; class participation grades and exam grades. Class participation grades are assigned by the teacher while exam grades are determined in agreement between the teacher and an external examiner. Teachers and examiners are instructed to give grades based on an absolute scale rather than grading on a curve.[8] Grades are based on the following scale: 0, 3, 5, 6, 7, 8, 9, 10, 11 and 13, where 0 is the lowest possible grade and 13 is the highest. Students need a grade point average of 6 or more to graduate and the recorded grade point averages of high school graduates therefore range from 6 to 13. The majority of exams take place just be-

[8]Grading on a curve would bias the observed treatment effects downward because school-wide increases in cognitive performance would not affect grades. Full relative grading would also imply that there are no year-to-year changes in average grades within schools. However, the standard deviation of average grades across years within the same school is 0.55. The overall standard deviation of grades is 1. Hence, relative grading is unlikely to bias the results.

fore graduation, and 60 percent of grades are determined during the last year of school. After graduation, the GPA determines which universities and tertiary courses students are eligible for acceptance into, and there is considerable incentive to perform well.[9]

Beyond educational outcomes, the data set includes a wide range of socioeconomic characteristics of the students and their parents. The administrative data covers the universe of Danish citizens dating back to 1980. Parental characteristics include income, education, age, labor market participation, and marital status. To avoid using bad controls – controls that may be influenced by the reforms – I measure parental control variables eight years prior to graduation. Student characterics include age, number of siblings, gender, school institution and municipality of residence. I also use data from health registers which contain information on the birth weight and birth length of all children born after 1973.

Because of a high school reform in 2008 and a large-scale municipality reform in 2007, the main analysis focuses on years prior to 2007.[10] Furthermore, because I measure parental controls eight years before graduation and parental controls are available from 1980, the main analysis period is 1988-2006.

The full sample consists of 544,023 STX students graduating during the years 1980-2011, while the main analysis sample consists of 308,718 STX students graduating during 1988-2006.

4 Empirical Method

I use an Intensity-of-Treatment Difference-in-Differences strategy to identify the causal effect of salt iodization on school performance in adolescence. This approach requires time-series variation in iodine intake and cross-sectional variation in treatment intensity. The time-series variation comes from the introduction of iodized salt in Denmark between 1998 and 2001. As a source of variation in treatment intensity, I exploit pre-existing differences in iodine deficiency.

[9]Grades in individual courses are only recorded from 1997. It is not possible to assess the importance of individual grades on the GPA because grades are given different weights in the calculation of the GPA and these weights are not recorded in the data. Neither is it possible to study grades by year of school as information on the timing of grades is only available from 2005.

[10]The high school reform introduced a new grading scale, different course structures, and additional requirements for cross-disciplinary activities. The municipality reform reduced the number of municipalities from 271 to 98.

The assumption is that the benefits of salt iodization are larger for students that are more iodine deficient.

I use the concentration of iodine in local drinking water as a measure of pre-existing iodine deficiency. All tap water in Denmark is derived from groundwater reserves, and the amount of iodine in groundwater is determined by time-invariant geological conditions (Voutchkova et al., 2015). Before the introduction of iodized salt, tap water accounted for 25 percent of the total iodine intake in Denmark (Rasmussen et al., 2000) and drinking water was one of the main drivers of regional differences in iodine deficiency (Rasmussen et al., 1996).[11] Geological conditions also affect the iodine concentration in milk, which accounts for another 25 percent of the total iodine intake (Rasmussen et al., 1996). In combination, these correlations produce a clear positive relationship between iodine in drinking water and iodine in urine - the most common measure of iodine intake (Pedersen et al., 1999).[12]

I measure the iodine concentration in drinking water using data from the Geological Survey of Denmark and Greenland (GEUS) on water works and groundwater analyses, which features 2,800 unique iodine samples from all parts of Denmark. The quality of groundwater in Denmark is generally high and drinking water is only treated using simple aeration and sand filtration, which preserves most of the natural level of iodine (Voutchkova et al., 2015).[13] To relate these measurements to the iodine intake of high school students, I match water works to the five nearest iodine samples and then collapse the data at the municipality level.[14,15] See Appendix A.2

[11]Bottled water consumption is very low in Denmark (Voutchkova et al., 2015).

[12]Other studies have used geographical variation in goiter incidence rather than iodine in drinking water as a measure of iodine deficiency, see Feyrer et al. (2017); Politi (2015, 2010). While goiter is a more direct measure of thyroid hormone deficiency, it is arguably a less exogenous one. Goiter is caused by low intake of milk and fish, and the use of goitrogens (goiter-inducers) such as alcohol and cigarettes. The consumption of each of these is correlated with socioeconomic status. In contrast, the iodine concentration in drinking water is solely determined by geological conditions. Therefore, using iodine concentrations in drinking water rather than goiter rates provides a more exogenous source of variation in iodine deficiency. Nonetheless, because drinking water is an important determinant of iodine intake, the two measures are highly correlated, see Feyrer et al. (2017). Because iodine deficiency was not considered a problem in Denmark throughout most of the 20th century, iodine deficiency disorders, including goiter, are not well recorded during the pre-reform period. Therefore, it is not possible to provide robustness checks using goiter rates as an alternative to iodine concentrations in drinking water.

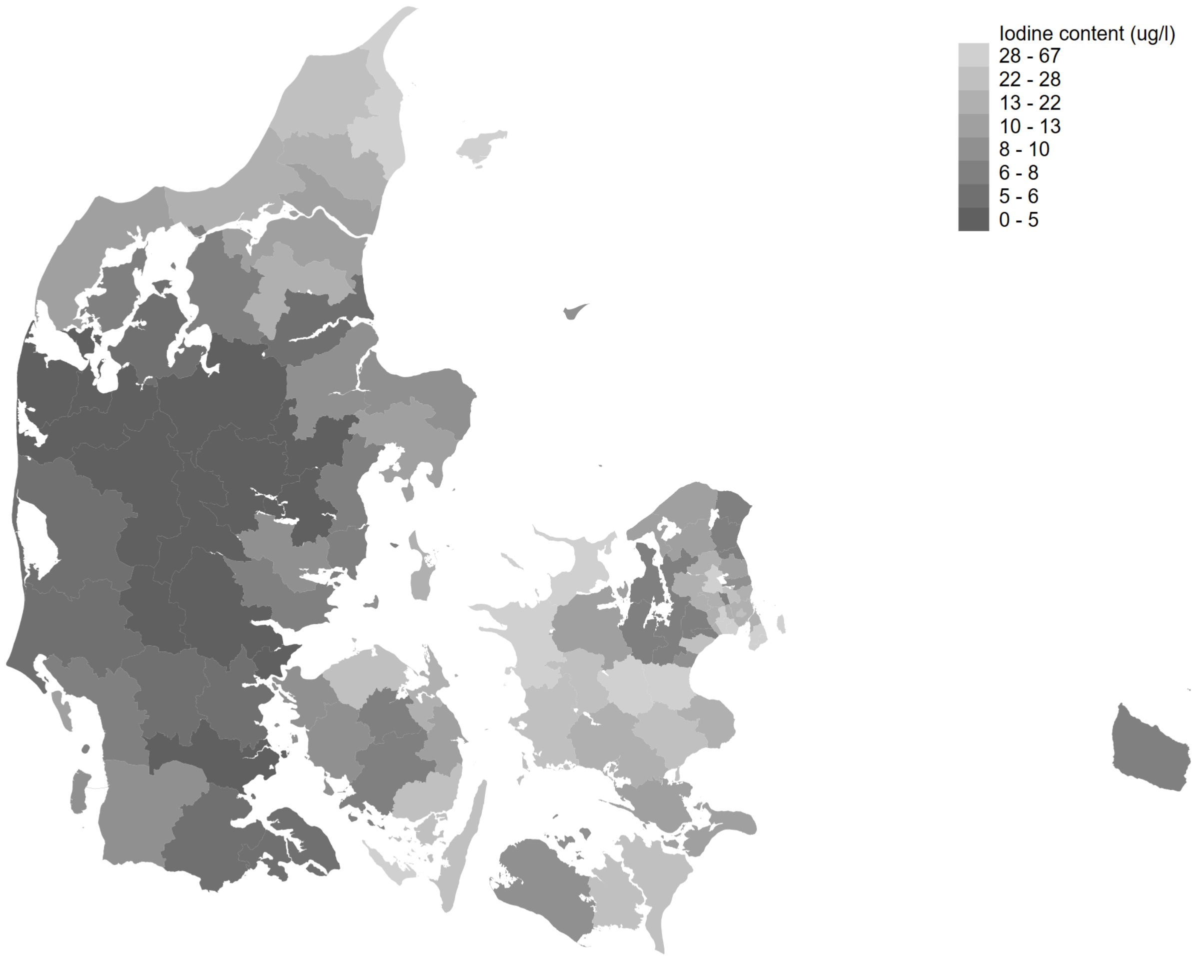
[13]There are no restrictions on iodine concentrations in drinking water in Denmark (Voutchkova et al., 2015).

[14]I match iodine samples to water works to account for the location of water works within municipalities.

[15]In 2007 a big municipal reform reduced the number of municipalities in Denmark from 271 to 98. To avoid this data break, I use post-2007 municipality borders throughout the analysis. I could use pre-2007 municipalities in the main analysis using the years 1988-2006. However, drinking water iodine concentrations are based on noisy

for a description of the approach. Municipalities are responsible for water supply and represent the smallest geographical unit available in the data. Furthermore, as shown in Appendix Figure A.3, the within-municipality variation in iodine concentrations in groundwater is limited.[16]

Figure 1: Iodine Concentration in Drinking Water in Danish Municipalities



Note: The figure shows the iodine concentration (μg/liter) in drinking water for each municipality in Denmark. Recommended iodine intake is 150 μg/day. The values are based on data from groundwater analyses by the Geological Survey of Denmark and Greenland (GEUS).

Figure 1 displays the derived iodine concentrations in drinking water across municipalities in Denmark. The geographical pattern closely resembles previous studies using direct drinking water samples.[17] The iodine concentration ranges from 1 μg/liter to 67 μg/liter. Hence, with

data and pre-2007 municipalities are rather small geographical units. Therefore, using pre-2007 municipalities rather than post-2007 municipality yields similar results, but increases the variance. In addition, many pre-2007 municipalities shared the same water works and the actual variation in iodine concentrations within post-2007 municipalities is therefore limited. See Appendix Figure A.3.

[16] Appendix Section A.4 discusses the implications of measurement error in iodine concentrations.

[17] See, for instance, Voutchkova et al. (2015), Figure 3, Panel A or Pedersen et al. (1999), Figure 1.

an average tap water consumption of 1.7 liter/day, drinking water accounts for 1 to 76 percent of the recommended iodine intake of 150 μg/day.[18] The lowest concentrations are found in Mid-West Denmark and the highest concentrations are found in North-West Denmark and East Denmark. Hence, while inhabitants in Mid-West Denmark get almost no iodine from drinking water, inhabitants in North-West Denmark and parts of East Denmark get up to 76 percent of the recommended iodine intake from drinking water.

I define two treatment intensity variables based on the drinking water data. (1) A discrete treatment variable equal to one for students living in municipalities with below median iodine concentrations in drinking water. (2) A continuous treatment variable specified as: $Treat = -log(IodineConcentration)$, following previous studies (Feyrer et al., 2017). The continuous specification captures the likely concave relationship between initial iodine intake and cognitive performance. Because the thyroid gland is able to partially compensate for insufficient iodine intake, mild iodine deficiency may not matter for cognitive performance, while moderate to severe iodine deficiency may have drastic consequences. In Appendix Section A.3, I show that the continuous specification provides a good fit of the observed relationship between iodine concentrations in drinking water and the municipality-level change in high school GPA.

I scale the continuous treatment variable such that the difference between the 95$^{\text{th}}$ and 5$^{\text{th}}$ percentile is equal to one. Therefore, the coefficients reflect the effect of going from the 95$^{\text{th}}$ to the 5$^{\text{th}}$ percentile of iodine concentrations in drinking water – from a mildly iodine deficient municipality to a moderately iodine deficient municipality.[19]

I estimate the effect of salt iodization using a standard Difference-in-Differences model. As high school students in Denmark graduate in late June and the two salt iodization reforms were implemented in June 1998 and between July 2000 and April 2001, the reforms were

[18] This number comes from (Pedersen et al., 1999), who regress iodine in urine – a common measure of iodine intake – on the iodine concentration in drinking water and find a well-fitted linear relationship of $IodineUrine = 43.2 + 1.7 * IodineWater$, where $IodineWater$ is measured in μg/liter and $IodineUrine$ is measured as μg/day. This is consistent with an average tap water consumption of 1.7 liters/day, which is reasonable since bottled water consumption is very low in Denmark (Voutchkova et al., 2015).

[19] Students living in areas in the 95$^{\text{th}}$ percentile have a predicted urinary iodine excretion, based on Pedersen et al. (1999), of $64\mu g/l$ compared to $33\mu g/l$ for students living in areas in the 5$^{\text{th}}$ percentile. Severe, moderate and mild iodine deficiencies are defined as iodine concentrations in urine below 20 $\mu g/l$, between 20 and 50 $\mu g/l$, and between 50 and 100 $\mu g/l$ (Andersson et al., 2012).

implemented too late in the year to affect the GPA of students who graduated in 1998 and 2000/2001. Therefore, the first students to benefit from the voluntary program in 1998 and the mandatory program in 2000-2001 graduated in 1999 and 2001/2002, respectively. The estimation model is as follows:

$$GPA_{it} = \pi_t + \omega_m + \beta_1 P1_t \times Treat_m + \beta_2 P2_t \times Treat_m + X_{it}\delta + \epsilon_{it}, \quad (1)$$

where GPA_{it} is the individual GPA of high school students graduating in year t, π_t are year dummies, ω_m are municipality fixed effects, $P1_t$ and $P2_t$ are dummies for post-reform years 1999-2001 and from 2002, $Treat_m$ is either the discrete or continuous treatment variable, X_{it} is a vector of controls and ϵ_{it} is an error term. I include the following control variables: *Parental characteristics:* Income percentile, years of schooling, age. I include separate controls for fathers and mothers. *Student characteristics:* Age, birth year, gender, number of siblings, birth order. All control variables are discretized and included in the regressions with dummies for each value to avoid assumptions on functional form.[20] Standard errors are clustered at the level of treatment (municipality) to allow for autocorrelation in errors (Bertrand et al., 2004).[21]

The β_1 coefficient reflects the treatment effect of the 1998 reform, while the β_2 coefficient reflects the combined treatment effect of the 1998 and 2000-2001 reforms. The identifying assumption is that outcomes in the treatment and control groups would have followed similar trends had it not been for the introduction of iodized salt. This common trend assumption is not directly testable, but I can assess its validity by studying differences in pre-trends. If the GPA of students in iodine-rich and iodine-poor municipalities follow similar trends prior to salt iodization, it is reasonable to assume that they would have continued to do so in absence of the reforms. Therefore, I also estimate regressions of the form:

$$GPA_{it} = \pi_t + \omega_m + \sum_{t \neq 1998} \beta_t I(year = t) \times Treat_m + X_{it}\delta + \epsilon_{it}, \quad (2)$$

[20]To include students with an unknown or dead parent, I add dummies for missing values.

[21]The significance of the results does not depend on the choice of cluster-robust standard errors. Appendix Table A.7 show results with standard errors clustered by high school, twoway clustering by high school and municipality, and by provinces – 11 large geographical areas.

Where the β_t coefficients reflect the difference in the average GPA of students across iodine-poor and iodine-rich municipalities over time.

Even with identical pre-trends, the common trend assumption is violated if, for reasons unrelated to salt iodization, the difference in grades between students in iodine-rich and iodine-poor municipalities changes when the reforms are introduced. There are two types of shocks that can cause such a bias: (1) Shocks to determinants of grades and (2) endogenous selection into high school across years. I discuss these concerns in the Robustness Section and argue that they do not pose a threat to the identification strategy.

A related issue concerns the impact of salt iodization on parents and the response of parental investments to the policy. If salt iodization has a positive effect on parental resources this might improve school performance of their children, regardless of whether the students themselves benefit from salt iodization. Moreover, for a given level of parental resources, an increase in the children's school performance might affect parental investments. If public investments, e.g. salt iodization, and parental investments are complements, parents will respond by increasing investments in children, thus magnifying the treatment effect. On the other hand, if the two types of investments are substitutes, parental investments will decrease and attenuate any treatment effect on children. Empirically, I cannot distinguish between the direct effect of salt iodization on children and the effects going through parents and parental investments. The estimated treatment effects thus represent a mix of both.

4.1 Summary statistics

Table 1 presents summary statistics of high school students who graduated during the pre-reform period 1988-1998. I split the data into treatment and control groups using the discrete treatment variable (below median iodine concentration in drinking water). Overall, the characteristics of the students are remarkably well balanced across the two groups.

Table 1: Summary Statistics of STX Graduates from 1988 to 1998

	Treatment (1)	Control (2)	Difference (3)	Difference, Within Region (4)
Student Characteristics				
Age	19.39	19.36	0.031	-0.035
	(0.65)	(0.74)	(0.029)	(0.023)
Male	0.40	0.42	-0.014*	0.004
	(0.49)	(0.49)	(0.007)	(0.006)
Number of Siblings	1.34	1.22	0.117***	0.020
	(0.86)	(0.85)	(0.033)	(0.029)
Science Track	0.62	0.62	-0.003	0.006
	(0.48)	(0.48)	(0.009)	(0.008)
GPA	8.33	8.32	0.008	0.016
	(0.94)	(0.96)	(0.019)	(0.016)
Parental Characteristics				
Number of Parents	1.98	1.97	0.004	0.002
	(0.15)	(0.16)	(0.003)	(0.002)
Parental age	48.1	48.2	-0.055	-0.020
	(4.6)	(4.6)	(0.102)	(0.091)
Parental Years of Schooling	13.3	13.4	-0.190	0.068
	(2.6)	(2.5)	(0.136)	(0.112)
Parental Wealth	467,399	488,279	-20,880	43,739
	(6,704,080)	(4,089,203)	(76,219)	(60,304)
Parental Income	514,211	537,700	-23,489	11,564
	(600,511)	(532,949)	(20,738)	(17,241)
Geographical Concentration[c]				
Densely Populated Area	0.20	0.33	-0.132	-0.031
	(0.40)	(0.47)	(0.146)	(0.115)
Intermediate Density Area	0.38	0.40	-0.011	0.017
	(0.49)	(0.49)	(0.126)	(0.151)
Thinly Populated Area	0.42	0.28	0.143	0.014
	(0.49)	(0.45)	(0.112)	(0.125)
Number of Observations	91,172	90,852	182,024	182,024

Note: Columns 1 and 2 display the mean characteristics of students in the treatment and control groups in the pre-reform years 1988-1998. Standard deviations are reported in parentheses. Column 3 presents the difference between the treatment and control groups, based on a regression of the specific characteristic on the discrete treatment variable. Standard errors clustered by municipality are reported in parentheses. Column 4 repeats this exercise, but controlling for a 'West Denmark'-dummy in the regression, such that coefficients reflect within-region differences between the treatment and the control groups. a) High school students choose between a Science or Humanities track. This variable is only recorded for the years 1988-2004. b) Wealth and income variables have been converted to 2011 levels using nominal GDP. c) The geographical categories follow from Eurostat's DEGURBA (Degree of Urbanization) classification. *** p<0.001 ** p<0.05, * p<0.1.

The average age of high school graduates in the treatment and control group is 19.39 and 19.36. More girls than boys graduate from the STX program, with only 40 percent boys in the treatment group and 42 percent in the control group. Students in the treatment and control group have, on average, 1.34 and 1.22 siblings, respectively. High school offers two tracks; Science and Humanities. Science students follow courses in Mathematics, Physics, and Chemistry, while Humanities students take classes in Latin, French, German, and Spanish. This choice variable is balanced across groups with 62 percent of the students enrolled in the Science track. The grade point averages of graduates – the outcome variable in the empirical analysis – range from 6 to 13, with an average of approximately 8.32 and a standard deviation close to one. Parental characteristics are also similar in the two groups. Parents in the treatment and control group are, on average, 48 years old and have around 13 years of schooling. However, parents in the treatment group have less wealth and lower income than parents in the control group.

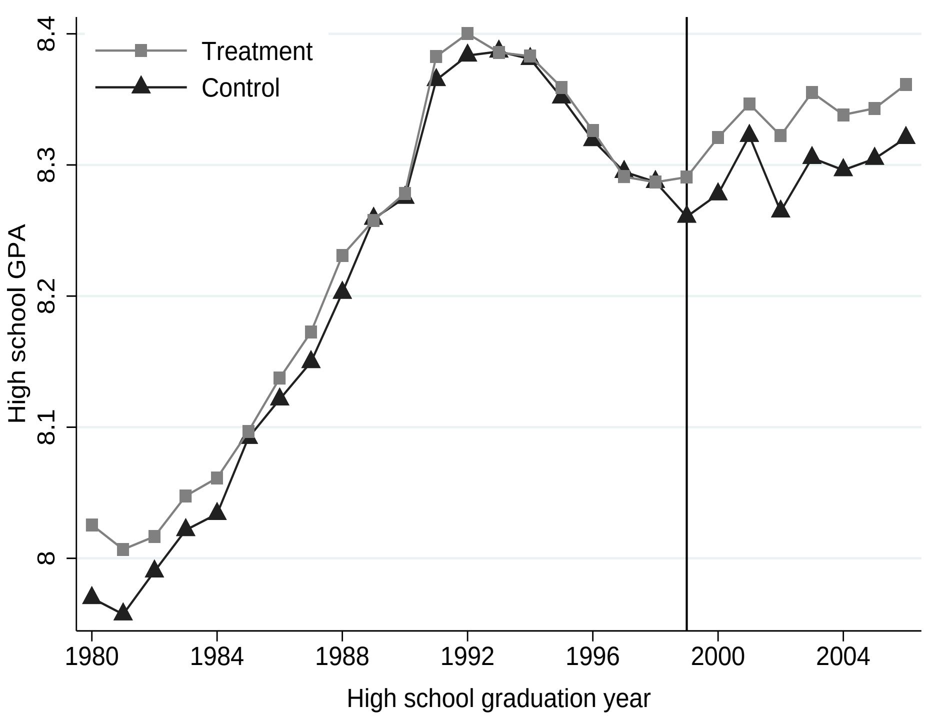
As shown in Figure 1, the majority of treatment municipalities are placed in West Denmark. On average, West Denmark is similar to East Denmark, but with more rural areas and a larger share of the work force employed in the industry and agriculture. The bottom rows of Table 1 show how municipality-specific population densities vary across the treatment and control group. The treatment group is more likely to live in rural areas than the control group. 42 percent of the students in the treatment group live in thinly populated areas, compared to 27 percent of the students in the control group.[22] As in most developed countries, regional differences in socio-economic outcomes in Denmark are largely due to rural/urban divides. Hence, even though the students' characteristics are well-balanced, one may worry that the treatment and control groups are exposed to different shocks, which may pose a threat to the analysis. In the Robustness Section, I add different kinds of region-by-year fixed effects to the regressions to show that the main results are robust to using only within-rural/urban area or within-West/East Denmark variation in treatment.

[22]The geographical groups are based on Eurostat's DEGURBA (Degree of Urbanisation) classification `http://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_DEGURBA`.

In column 4 of Table 1, I reestimate differences in characteristics, controlling for whether the student lives in West or East Denmark. The coefficients are either insignificant or have the opposite sign to the raw differences in column 3. The differences in population density also largely disappear. Hence, even though treatment assignment is not random, it is not systematically related to characteristics of the students.

5 Results

Figure 2: Trends in Grade Point Averages Before and After Salt Iodization

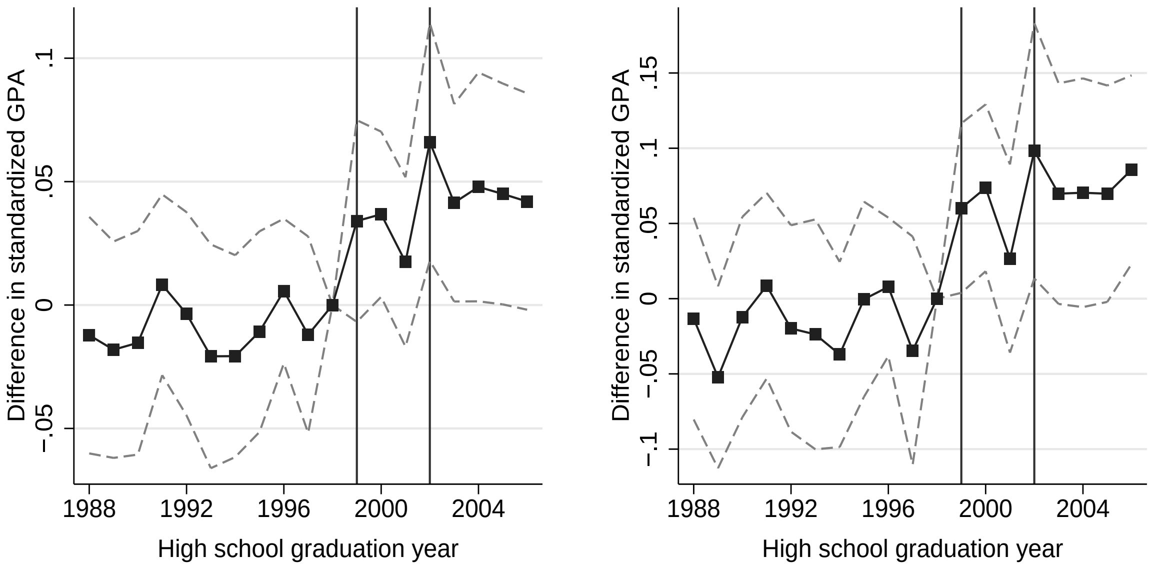


Note: The figure plots the average GPA among high school graduates in the treatment and control groups for each year during the period 1980-2006. The vertical line at year 1999 marks the introduction of iodized salt.

Figure 2 displays the average GPA of high school graduates in the treatment and control group for each year during the period 1980-2006, without the addition of control variables or municipality fixed effects. The average GPA is slightly higher in the treatment group than in the control group throughout the pre-reform period. If the students were randomly assigned to the treatment and control group, we would expect the opposite – that iodine deficiency is associated with lower grades. However, the Difference-in-Differences method does not require random assignment but only that the common trend assumption is satisfied. Grades in the treatment and control groups evolve in parallel throughout the entire 19-year pre-reform period, although the gap between two groups narrows slightly over time. Overall, Figure 2 suggests that the common trend assumption is valid and that grades in the two groups would have continued to mimic each other had it not been for the introduction of iodized salt.

Turning to the effects of salt iodization, it is clear from Figure 2 that grades in the treatment group increase relative to the control group from 1999 and onward. This is consistent with the timing of the first salt iodization reform and the hypothesis that iodine deficiency impairs cognitive performance in adolescence.

Figure 3: Difference in Grade Point Averages Across Iodine-Poor and Iodine-Rich Areas Over Time



A Discrete **B** Continuous

Note: The figure plots the difference in the average standardized GPA between iodine-poor and iodine-rich areas for each year during the period 1988-2006, relative to the base year 1998. The dotted grey lines represent 95 percent confidence intervals using standard errors clustered by municipality. Panel A shows results for the discrete treatment variable, panel B shows results for the continuous treatment variable. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization. All control variables are included as dummies.

Figure 3 plots the difference in the average standardized GPA across iodine-poor and iodine-rich areas over time, using specification (2). As in Figure 2, the difference in GPA is stable across years, using both the discrete and continuous measure of treatment. More interestingly, Figure 3 exhibits two upward shifts in grades in 1999 and 2002, consistent with the voluntary

Table 2: The Effect of Salt Iodization on the Grade Point Averages of High School Students

	Discrete	Continuous
First Reform	0.039***	0.070***
	(0.012)	(0.017)
Second Reform	0.057***	0.094***
	(0.013)	(0.020)
Observations	308,718	308,718
P-value: $1^{st} = 2^{nd}$ reform:	0.133	0.217
R^2	0.120	0.120

Note: The estimates reflect the differential change in the standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). Column 1 shows the results for the discrete treatment variable, column 2 shows the results for the continuous treatment variable. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. All control variables are included as dummies. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

program in 1998 and the mandatory program in 2000-2001. This suggests that the iodized salt policies produced an immediate improvement in school performance among adolescents.

Table 2 reports the Difference-in-Differences estimates. When considering the combined effect of the two reforms, shown in row 2, I find that salt iodization increases the GPA of high school students in iodine-poor areas by 5.7 percent and 9.4 percent of a standard deviation, for the discrete and continuous measures of treatment.

Recall that the discrete treatment variable identifies the difference in the effect of salt iodization between students living in areas with iodine concentrations in drinking water below and above the 50^{th} percentile, while the coefficient on the continuous treatment variable reflects the difference when going from the 95^{th} to the 5^{th} percentile. The two coefficients are, therefore, not directly comparable.[23]

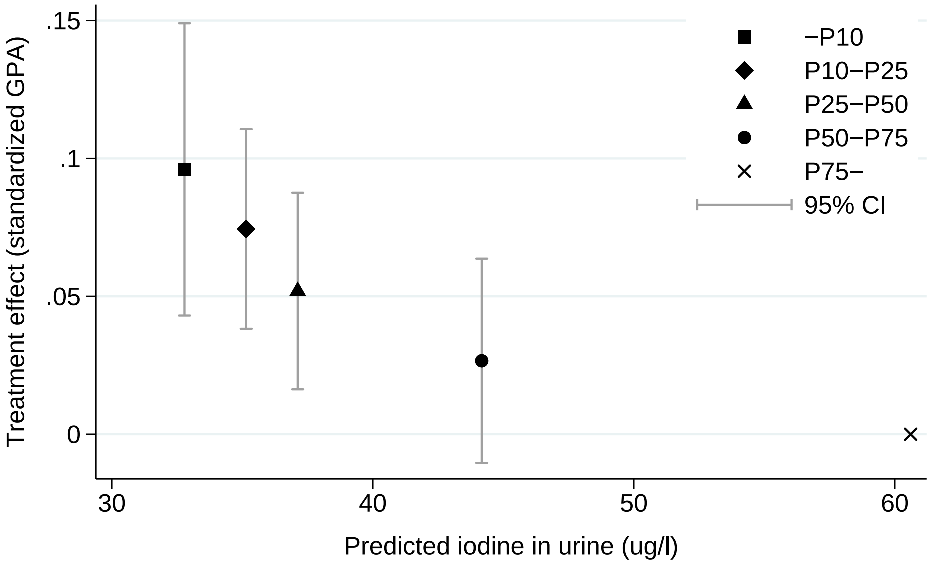
Table 2 also reports the effect of the first salt iodization reform (row 1), compared to the effect of both reforms (row 2). Two-thirds of the increase in grades is caused by the first and voluntary reform. Hence, even though the first reform only increased iodine intake by 10 $\mu g/day$ (Laurberg et al., 2009), compared to 40 $\mu g/day$ in the second reform, the first reform had a larger impact on school performance than the second reform. This suggests that the relation-

[23] If I compare the predicted treatment effect for students in municipalities with iodine concentrations below vs. above the median for both treatment variables, they provide very similar results, see Appendix Section A.3.

ship between iodine intake and cognitive performance is very concave. To test this, I estimate the benefits of salt iodization across the distribution of initial iodine intake.

I reestimate treatment effects with four treatment groups based on the distribution of iodine in drinking water: 1st-10th percentile, 10th-25th percentile, 25th-50th percentile, 50th-75th percentile. I use municipalities with iodine concentrations in drinking water above the 75th percentile as a control group.

Figure 4: Heterogeneity by Degree of Iodine Deficiency



Note: The figure plots the change in the average standardized GPA from 1988-1998 (pre-reform) to 2002-2006 (post-reform) of high school students living in municipalities belonging to different parts of the distribution of iodine concentrations in urine, relative to students in municipalities above the 75th percentile. Iodine in urine is predicted using drinking water iodine concentrations and estimates from Pedersen et al. (1999). Standard errors are clustered by municipality. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. All control variables are included as dummies.

Figure 4 plots the estimated treatment effects against iodine concentrations in urine, which I predict using estimates from Pedersen et al. (1999).[24] Severe, moderate and mild iodine deficiencies are defined as iodine concentrations in urine below 20 $\mu g/l$, between 20 and 50 $\mu g/l$, and between 50 and 100 $\mu g/l$ (Andersson et al., 2012). Clearly, the relationship between treatment effects and initial iodine intake is non-linear. The control group – municipalities above

[24] Pedersen et al. (1999) estimate the relationship between iodine in urine and iodine in water: $IodineUrine = 43.2 + 1.7 * IodineWater$, where $IodineWater$ is measured in μg/liter and $IodineUrine$ is measured as μg/day. To convert the predicted iodine in urine to μg/liter, I assume an average adult daily urine output of 1.5 liters.

the 75th percentile – is mildly iodine deficient with a predicted iodine concentration in urine of 60 $\mu g/l$. The iodine concentration in urine in municipalities in the 50th to 75th percentile is 16 $\mu g/l$ lower than in the control group and the treatment effect for these students is 0.027 standard deviations and not statistically significant. The iodine concentration in urine in municipalities below the 10th percentile is 27 $\mu g/l$ lower than in the control group and the treatment effect for these students is 0.096 standard deviations and highly statistically significant. This pattern is consistent with a very concave relationship between iodine intake and cognitive performance, where the benefits of salt iodization are concentrated among individuals with moderate to severe iodine deficiency.

In Appendix Section A.5, I estimate the effect of in utero exposure to salt iodization in Denmark and provide suggestive evidence that cohorts born after the first iodization policy obtained higher math grades in lower/middle secondary school. Furthermore, Appendix Section A.1 shows that among the elderly the first salt iodization reform caused an increase in hyperthyroidism cases, which is a known negative side-effect of increasing iodine intake. Both of these analyses support my main results and show that even though the first and voluntary salt iodization reform was unsuccessful at eliminating iodine deficiency, it was successful at alleviating the worst consequences thereof.

In the rest of the paper, I focus on estimates using the continuous treatment variable. The continuous treatment variable uses the available variation in drinking water iodine more efficiently than the discrete treatment variable, and the functional form of the continuous treatment variable accurately fits the observed relationship between the benefits of salt iodization and drinking water iodine, see Appendix Figure A.4. The results for the discrete treatment variable are qualitatively similar and provided in Appendix Section A.7.

5.1 Heterogeneous Treatment Effects

Iodine deficiency disorders are much more prevalent among women than men (Pedersen et al., 2002; Vanderpump, 2011) and a number of studies find larger effects of in utero exposure to iodine deficiency among women (Field et al., 2009; Politi, 2010; Adhvaryu et al., 2020). The medical reasons for this gender difference is not well understood. Nonetheless, in line with previous studies, Appendix Table A.2 shows that the total effect of the salt iodization reforms is larger for girls than boys. The difference across genders is, however, not statistically significant.

Figure 5 shows the effect of salt iodization on different parts of the distribution of grades, estimated using quantile regression. I use the Jittering method (Machado and Santos Silva, 2005), which allows for discrete outcome variables, because the recorded GPA of students is rounded to one decimal point and the magnitude of treatment effects is close to one decimal point.[25] The Jittering method is computationally demanding. Therefore, I do not include control variables and I pool years in groups of three.

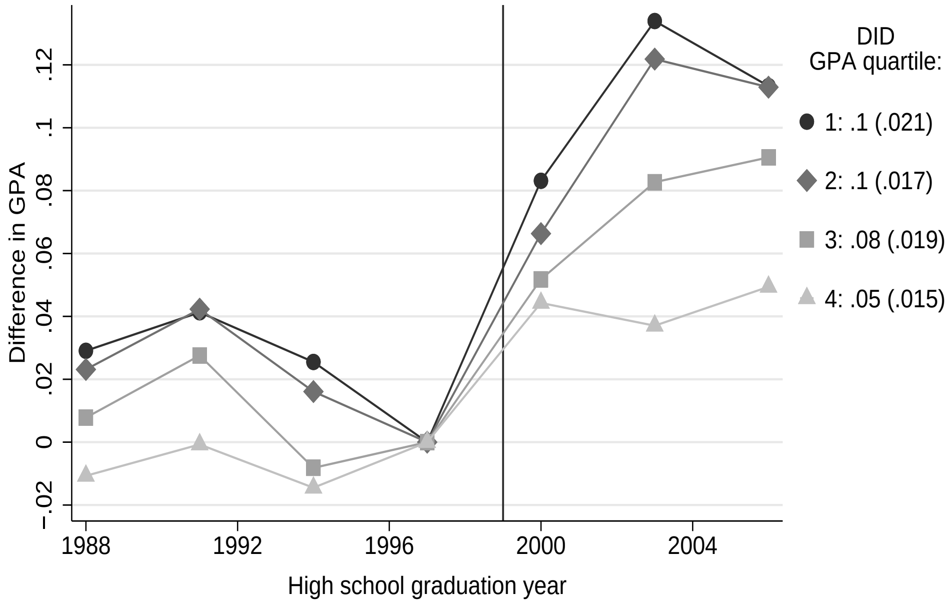
The lines in Figure 5 represent the difference in the first, second, third and fourth quartile of grades across iodine-poor and iodine-rich areas for each year during 1988-2006. The coefficients for the four quartiles are all fairly stable during the pre-reform period and then increase in 2000 (1999-2001), when salt iodization is introduced.

There are large differences in the effect of salt iodization across grade quartiles, with larger improvements in the bottom of the distribution of grades. Figure 5 reports the Difference-in-Differences estimates for each quartile. The effect on the first quartile of grades is twice as large as on the fourth quartile of grades and the difference between the two estimates is statistically significant at a 10 % confidence level.[26] Hence, students in the bottom of the grade distribution benefit most from salt iodization. This is at odds with the predictions of James Heckman's seminal work on skill formation in different periods of childhood (Cunha and Heckman, 2007), which posits that returns to investments in adolescence increase with initial skills. My findings suggest that human capital policies, in particular nutritional policies, in adolescence may reduce initial disadvantage and reduce inequality in economic outcomes.

[25] Figure 5 reports the marginal effects at the average on the smoothed outcome variable (Z in Machado and Santos Silva (2005)).

[26] This is based on standard errors bootstrapped using 500 repetitions and clustered sampling by municipality. However, to make this computationally feasible I use only one repetition in the Jittering method. In other words, I estimate standard quantile regressions by adding noise to the discrete outcome variable, but do not take the average estimate over many different draws of the noise.

Figure 5: Effect of Salt Iodization on Different Quartiles of Grade Point Averages



Note: The figure shows the difference in the first, second, third and fourth quartiles of GPA across iodine-poor and iodine-rich areas during the period 1988-2006 using the continuous treatment variable. The coefficients are estimated with quantile regression using the Jittering method with 1,000 repetitions (Machado and Santos Silva, 2005). Years are pooled in groups of three; e.g., the coefficient in 1991 is based on the years 1990, 1991, and 1992. Estimates are relative to the baseline level in 1997. Difference-in-Differences estimates are reported to the right. These reflect the effect of salt iodization on each GPA quartile. No control variables are included in the regressions. Misspecification-robust standard errors are reported in parentheses. Cluster-robust standard errors have not been developed for the Jittering method. If I instead estimate the coefficients using just one repetition and standard quantile regression with standard errors clustered by municipality, the estimates and standard errors are: 0.11 (0.025), 0.09 (0.023), 0.08 (0.024), 0.05 (0.030) from the first to fourth quartile of grades.

Although the improvements in grades are largest in the bottom of the distribution of grades, the share of high school students who graduate does not change in response to the reforms, see Appendix Figure A.9.[27]

5.2 Mechanisms

Having established that salt iodization improves cognitive performance in adolescence, I now turn to the question of why this is. There are two mechanisms through which iodine deficiency can affect cognition; 1) through the effect of iodine deficiency on metabolic functioning and brain activity and 2) through brain damage induced by disturbances to normal brain development. I make two separate empirical predictions based on the mechanisms:

[27] One likely explanation is that students who do not graduate from high school because of low grades represent a small share of total dropouts. Because grades of non-graduates are not recorded in the data, these individuals cannot be separately identified. Overall, around 90 % of students who start high school end up graduating.

Metabolic Functioning

If the adverse consequences of iodine deficiency arise through an effect on the metabolism, the treatment effect from salt iodization should be independent of the age at which the students are first treated, as, within this mechanism, only current iodine intake matters for cognitive performance.

Brain Development

If the effects of iodine deficiency work through disturbances to normal brain development, each year a person lives with iodine deficiency during childhood has an independent negative long-run impact on cognitive ability in high school. Therefore, the treatment effect from salt iodization should be higher for students first treated earlier in life, who are protected from more years of brain damage. Specifically, if we assume that the incremental damage of one year of iodine deficiency during childhood does not depend on age, cumulative treatment effects decrease linearly with the age at which students are first treated.[28,29,30]

I test the predictions of the two competing mechanisms by running the baseline regressions for the extended period 1988-2011. Since high school students are, on average, 19 years old when they graduate, students who finished high school in 2011 were 6 years old when the first reform was implemented in 1998. Hence, at the time of their final exams, students who graduated in 2011 had been treated since age 6, whereas students who graduated in 1999 had been treated since age 18. I can, therefore, compare the effect of salt iodization on children first

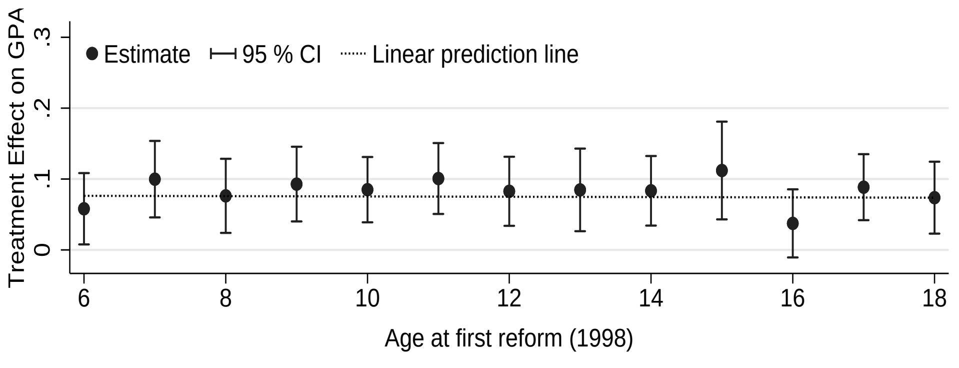
[28] Importantly, a different and indirect long-run effect could arise from dynamic complementarities and learning effects – improved learning in lower/middle school might lead to higher grades in high school.

[29] If salt iodization does have long-run benefits on cognitive ability, the reforms could crowd-out investments from parents and schools. In the extreme, this could lead to constant net effects on grades in high school, even if the benefits of salt iodization, in isolation, are larger for students exposed earlier in life.

[30] This prediction relies on the assumption that the treatment effect from one year of exposure to salt iodization is the same for all ages during childhood. There are several reasons why this might not be the case. (1) For a given degree of deficiency, iodine deficiency is likely to be more detrimental for brain development in early childhood than in late childhood, as brain development is more rapid early in life (Gilmore et al., 2018). However, this means that treatment effects should decrease with exponential decay rather than linearly with the age at which the students are first treated. (2) The degree of iodine deficiency is not necessarily constant by age. If children aged 6-17 years are not iodine deficient, that could explain why I do not observe long-run benefits of exposure to salt iodization in these ages.

treated at ages 6-18 by estimating separate treatment effects for students who graduated during 1999-2011.

Figure 6: Treatment Effects by Age at Introduction of Iodized Salt



Slope of Prediction Line and Tests of the Mechanisms

Intercept	Slope	Test 1 (slope=0)	Test 2 (intercept=slope)
0.0737	0.0002	0.9039	0.0004
(0.0190)	(0.0018)		

Note: The figure plots estimates of the effect of salt iodization on the standardized high school GPA of students first affected by iodized salt at the ages 6-18, using the continuous treatment variable. Each point is a separate Difference-in-Differences estimate for students who graduated in the post-reform years 1999-2011. Students who graduated in 1999-2011 were, on average, 18-6 years old when the first salt iodization reform was implemented in 1998. Hence, the coefficient for age 6 (age 18) in the figure is the Difference-in-Differences estimate for students who graduated in 2011 (1999). The table reports estimates of the slope and intercept of a linear regression going from age 18 to age 6. The intercept is the estimated treatment effect for students first treated at age 18, and the slope is the effect of an additional year of exposure to salt iodization during childhood. Columns 3 and 4 report the p-value of a t-test for whether the slope is different from zero and the p-value of an F-test for whether the intercept is equal to the slope. Standard errors are clustered by municipality. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects.

If the common trend assumption holds throughout the period, this straightforward empirical approach is able to identify all cumulative effects of correcting iodine deficiency at ages 6 to 18 on grades in high school. This encompasses the age interval considered by Gordon et al. (2009) and Zimmermann et al. (2006), who use randomized experiments to study short-run effects of iodine supplementation on cognitive performance.

Figure 6 plots the treatment effects for students first treated at ages 6 to 18 (graduated during 1999-2011). To test the two mechanisms, I fit a linear prediction line through these points and estimate the relationship between treatment effects and age of first exposure to salt iodization. The intercept measures the baseline effect on individuals first treated at age 18. The slope represents the additional long-run effect of having been exposed to salt iodization at an earlier age. The first mechanism implies that treatment effects are constant across ages and that the slope of the prediction line is zero. The second mechanism implies that treatment effects accumulate and increase linearly from ages 18 to 6, with a slope equal to the intercept.[31] As shown in Figure 6, the treatment effects on high school GPA are not larger for students first exposed to iodized salt at an earlier point in life. The slope of the prediction line is not significantly different from zero and I can clearly reject that the slope of the prediction line is equal to the intercept.

These results suggest that while the in utero consequences of iodine deficiency work through disturbances to normal brain development, the consequences of iodine deficiency in childhood and adolescence documented in this and related papers (Gordon et al., 2009; Zimmermann et al., 2006) are caused by an entirely different biological mechanism. One likely candidate is the effect of iodine deficiency on the metabolism, with short-run consequences for brain activity, memory, and concentration.

6 Robustness

The two main threats to the identification strategy are contemporaneous shocks to determinants of grades and endogenous selection into high school across years. As a first step, I address these concerns by including an extra set of control variables in the regressions. Appendix Table A.4 shows that including labor market controls for parents or controls for health of the students at birth, measured using birth weight and birth length dummies, does not impact the results. This suggest that changes in the composition of parental characteristics or initial endowments of the students are unlikely to drive the results.

Appendix Table A.5 reports estimates from family fixed effects regressions, in which treatment effects are identified using only variation between siblings. This accounts for any time-invariant family characteristics, but increases the variance of the estimates. The family fixed

[31] Under the assumption that the incremental damage of one year of iodine deficiency during childhood does not depend on age, the effect of preventing one additional year of brain damage during childhood, the slope, is the same as the treatment effect on students exposed one year before graduation, the intercept.

effects estimates are smaller, but not statistically significantly different from the baseline estimates.

The treatment group is concentrated in a few areas. Therefore, the results might be sensitive to regional shocks coinciding with the introduction of iodized salt. To address this concern, I include region-by-year fixed effects in the regressions. In doing so, the effect of the reforms is identified using only within-region variation in treatment, which eliminates the influence of any region-specific shocks. I use three different geographical control variables; the Degree of Urbanization (DEGURBA) classification from Eurostat, an extended DEGURBA classification created by Statistics Denmark, and a dummy indicating whether the student lives in West or East Denmark.[32] I use the West Denmark split because the majority of treatment group municipalities are placed in West Denmark, see Figure 1.

Table 3 presents the regression estimates. As reported in the summary statistics in Table 1, students in the treatment group are more likely to live in rural areas than students in the control group. To quantify how much of the variance in treatment assignment is actually explained by these differences, the last row of Table 3 reports the r-squared from a regression of the continuous treatment variable on the geographical control variables.

The degree of urbanization classifications explain between 8 and 15 percent of the variation in the continuous treatment variable. Even though this means that a large part of the variance in treatment assignment comes from comparisons across rural and urban areas, the results are not sensitive to excluding this source of variation and using only within-rural/urban area variation to identify the treatment effect. Regardless of the urbanization classification used, the estimates are close to the baseline results, albeit slightly smaller. The smaller coefficients may reflect that including the geographical controls worsens the attenuation bias from measurement

[32]The DEGURBA classification by Eurostat splits municipalities into three categories; (1) densely populated areas, (2) intermediate density areas and (3) thinly populated areas, `http://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_DEGURBA`. The extended DEGURBA classification by Statistics Denmark, splits intermediate density areas and thinly populated areas in Eurostat's classification into five groups based on the number of inhabitants – a total of six degrees of urbanization. West Denmark is defined as Jutland and Funen.

error in the treatment variables.[33,34] This is particularly likely in column 4 of Table 3, which reports the estimates using only within-West/East Denmark variation in treatment. The West Denmark dummy explains 25 percent of the variation in the continuous treatment variable. The estimated coefficients are smaller than the baseline estimates but they remain economically and statistically significant. The total effect of the two reforms is 6.4 percent of a standard deviation.

Table 3: Robustness to Geographical Control Variables

	(1)	(2)	(3)	(4)
First Reform	0.070***	0.070***	0.069***	0.049***
	(0.017)	(0.017)	(0.018)	(0.019)
Second Reform	0.094***	0.085***	0.085***	0.064***
	(0.020)	(0.021)	(0.021)	(0.024)
Baseline	X	X	X	X
DEGURBA 1		X		
DEGURBA 2			X	
West Denmark				X
Observations	308,718	308,718	308,718	308,718
R^2	0.120	0.120	0.120	0.120
P-value, dif. 1st reform		0.909	0.966	0.092
P-value, dif. 2nd reform		0.201	0.325	0.037
R^2 of Treat		0.063	0.105	0.283

Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row), using the continuous treatment variable. Baseline controls: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. DEGURBA 1: Dummies for the three categories in Eurostat's DEGURBA classification interacted with graduation year dummies. DEGURBA 2: Dummies for the five categories in Statistics Denmark's extended DEGURBA classification interacted with graduation year dummies. West Denmark: Dummy for living in Jutland or Funen (West Denmark) interacted with graduation year dummies. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

In Appendix Section A.4, I derive a ballpark estimate of the degree of measurement error in the treatment variables, which suggests that the baseline estimates are significantly downward-biased and that the true treatment effects are around 1.6 times larger. Furthermore, I derive theoretical predictions of the increase in the attenuation bias caused by the inclusion of region-

[33] The treatment variables are measured with substantial error. Even in the unlikely case that the groundwater samples perfectly predict actual iodine intake from drinking water, there are many other determinants of iodine deficiency.

[34] Region-by-year fixed effects worsens the attenuation bias because it reduces the true variation in the treatment variables without reducing the variation of the measurement error. See Appendix Section A.4 for a thorough discussion.

by-year fixed effects and show that the change in coefficients in Table 3 is consistent with these predictions.

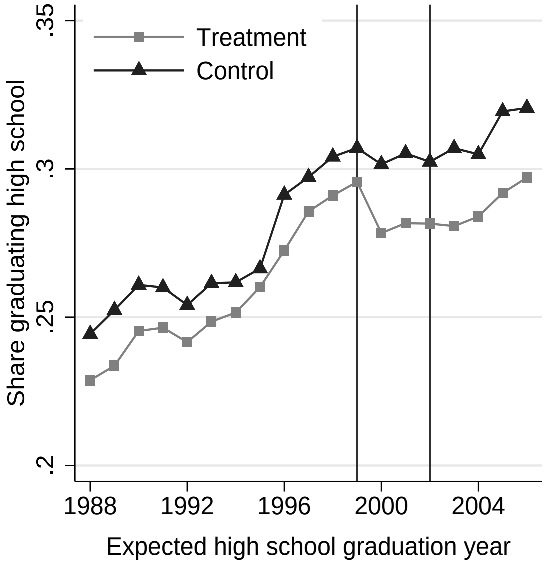
6.1 Sample Selection

High school is voluntary in Denmark and about 30 percent of a cohort choose to enroll in the STX program after finishing lower/middle secondary school.[35] Since the data only contains information on the GPA of STX graduates, differential selection into high school across years might affect the results. Figure 7A plots the share of lower/middle secondary school graduates that finish an STX high school education in treatment and control group municipalities, defined using the discrete treatment variable. I plot the graduation rates by the predicted graduation year to show when we can expect selection into high school to affect average grades. The predicted graduation year is set to three years after lower/middle secondary school graduation, at which point 90 percent of high school students graduate.

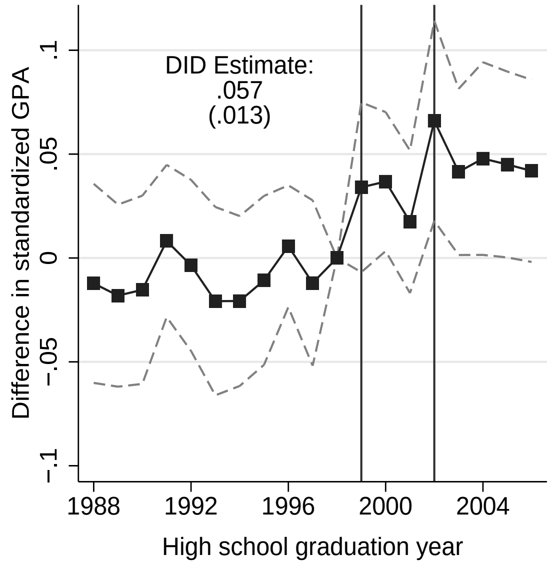
Throughout the data period, children in treatment group municipalities are less likely to obtain an STX high school education than children in control group municipalities. The gap narrows over time and then broadens in 2000, with a larger drop in graduation rates in treatment group municipalities. If marginal high school students would have achieved grades below those of the average graduate, the widening of the gap in graduation rates in 2000 may produce a mechanical increase in grades in the treatment group relative to the control group. However, since the effect on grades in the main results, shown in panel B, starts in 1999, the results cannot be explained by a change in graduation rates in 2000.

[35] In Denmark, school attendance is compulsory until the end of year 9. Children attend primary school ('Folkeskole') from kindergarten to year 9, which encompasses primary and lower/middle secondary education. High school refers to years 10 to 12.

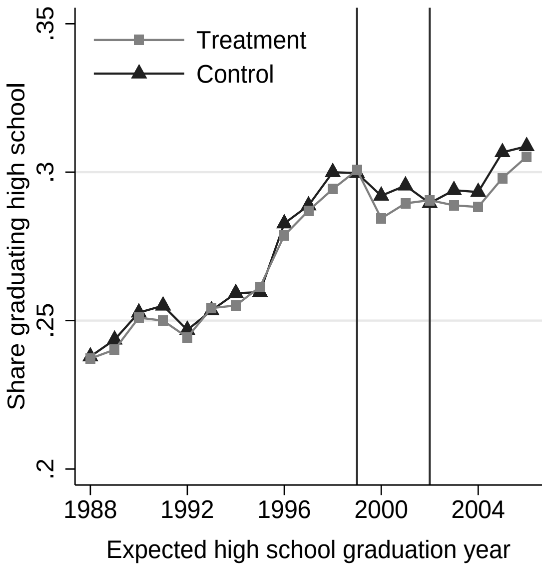
Figure 7: Sample Selection



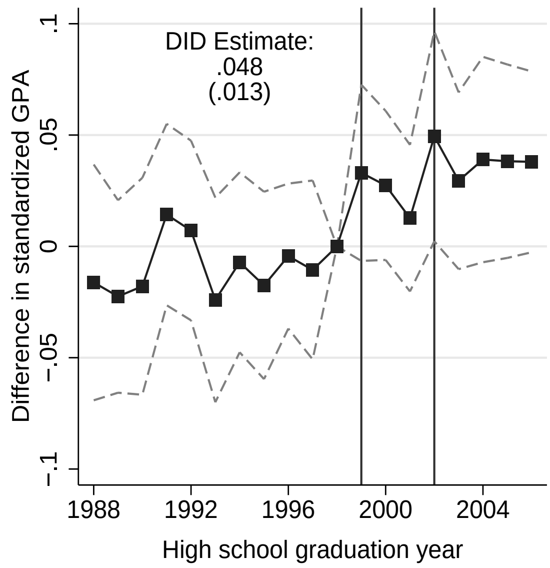
A Sample Selection, Raw



B Effect on GPA, Raw



C Sample Selection, Matched



D Effect on GPA, Matched

Note: Panel A reports the share of lower/middle secondary school graduates in treatment and control group municipalities that graduate from an STX high school education. I plot this for each expected high school graduation year (three years after leaving lower/middle secondary school) during the period 1988-2006. Panel B shows baseline estimates of the difference in average standardized GPA between the treatment and control groups for each year during 1988-2006, using the discrete treatment variable. The dotted grey lines represent 95% confidence intervals, using standard errors clustered by municipality. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization. Panels C and D replicate panels A and B, but on a matched sample. The matching is based on Inverse Probability Weighting. The propensity score P is estimated with Probit, using high school enrollment rates for each municipality and for each year as explanatory variables. I take the propensity score as given in the estimation of standard errors. The weights are $\frac{1}{P}$ for the treatment group and $\frac{1}{1-P}$ for the control group.

In Appendix Figure A.10, I show that the widening gap in graduation rates in 2000 is caused by a reduction in the number of schools offering the business-oriented HHX high school program in control group municipalities.[36] With fewer schools offering HHX programs, more individuals chose to enroll in the STX program, making the 2000 drop in STX high school graduation rates smaller in control group municipalities. If I drop municipalities that experienced a school closure during this period, the difference in graduation rate levels and trends disappear, while the original results on grades remain, see Figure A.10.

Furthermore, in Appendix Figure A.11, I predict the GPA of students based on the full set of control variables and show that there is no change in this summary measure of observable characteristics of students around the introduction of iodized salt. In addition, Appendix Table A.6 shows that the main results are robust to including municipality-level pre-reform shares of lower/middle secondary school graduates enrolling in the STX, HHX, HTX and HF high school programs interacted with year. This accounts for the potential concern that effects are driven by areas with a tradition of preferring one type of high school program over another. In summary, the results are unlikely to be driven by changes in the composition of students graduating from high school around the time of the reforms.

To show more formally that sample selection is not an issue, I match treatment and control municipalities based on STX high school graduation rates. If the results are caused by sample selection, the effect on grades would be zero if graduation rates were identical in the two groups. By matching on graduation rates I can test this scenario and evaluate whether sample selection drives the results.

I use Inverse Probability Weighting (Mansournia and Altman, 2016) to conduct the matching. I estimate the propensity score by Probit and use STX high school enrollment rates in

[36]HHX is the second-largest high school program and around 10 percent of a lower/middle secondary school cohort enroll in the HHX program after graduation. The reduction in the number of high schools offering HHX programs in control group municipalities around 2000 is most likely due to relatively small cohorts in those years.

each municipality and for each expected graduation year during 1988-2006 as explanatory variables.[37] The results are shown in Figure 7, panels C and D.

The matching is accurate. As shown in Figure 7C, there is no visible gap in graduation rates between treatment and control group municipalities in the matched sample. More importantly, there is no widening gap from 2000 and onward. Nonetheless, the effect on grades, shown in panel D, persists. The estimated treatment effect is close to the baseline effect for the discrete treatment variable reported in panel B. This shows that sample selection cannot explain the results of the empirical analysis.

6.2 External Validity

This paper estimates the causal effect of salt iodization on cognitive performance among Danish high school students. A natural question is whether this sample is representative of the general population in Denmark and how the results for Denmark relate to salt iodization policies in other parts of the world.

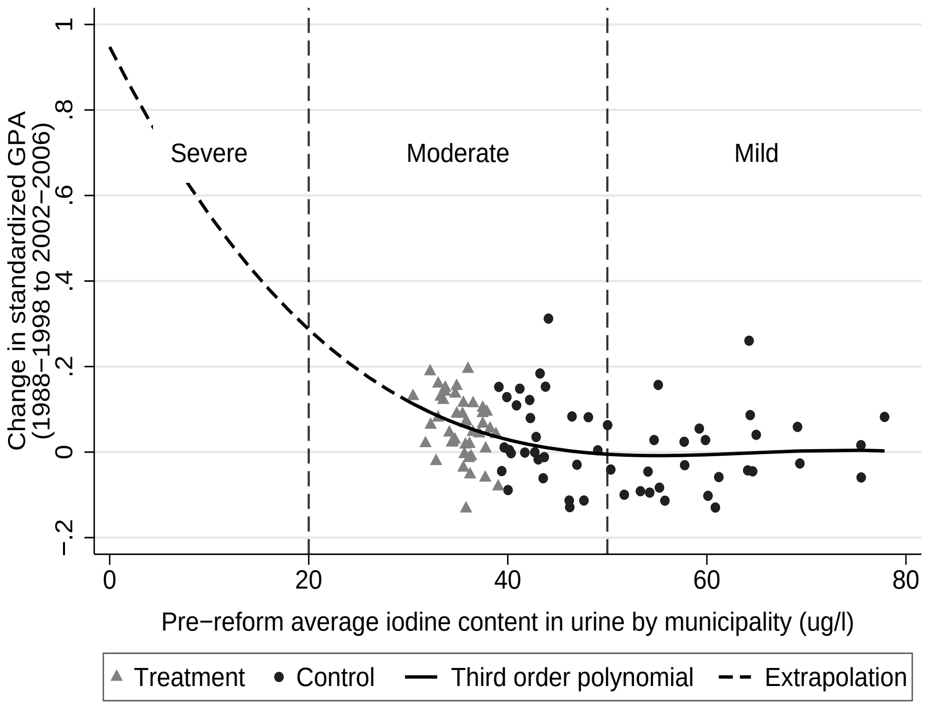
Because upper secondary education is voluntary in Denmark and most high school graduates go on to complete a tertiary education, high school students represent a positively selected sample of higher-achieving individuals. Since high-achieving students benefit less from salt iodization than low-achieving students, see Figure 5, I expect larger estimates for the general population of adolescents. Hence, given that the estimates for high school students are internally valid, they most likely represent lower bounds on the population-wide benefits of salt iodization in Denmark.

The results in this paper are specific to the degree of iodine deficiency present in Denmark prior to salt iodization. The Danish population was mildly to moderately deficient before the introduction of iodized salt. To give some indication of the benefits of salt iodization in other countries, I perform an extrapolation. I do this based on the relationship between the change

[37] I match on enrollment in high school rather than completion because the probability of dropping out of high school can be endogenous to treatment.

in average GPA over time and the pre-existing level of iodine deficiency across municipalities, measured using the predicted iodine concentration in urine.[24]

Figure 8: Predicted Gains from Correcting Iodine Deficiency by Degree of Deficiency



Note: The figure plots the change in average standardized GPA from 1988-1998 to 2002-2006 for each municipality in the sample relative to a municipality with mild iodine deficiency (80 μg/liter). The x-axis shows the iodine concentration in urine (a measure of iodine intake) in each municipality as predicted by the iodine concentration in drinking water. The solid and dashed line is the prediction and extrapolation of a third order polynomial. The dashed lines represents thresholds for mild, moderate and severe iodine deficiencies, see Andersson et al. (2012). For expositional purposes I remove a small outlier, the Municipality of Læsø, with an iodine concentration in urine of 105 μg/liter.

This exercise is merely an illustration of the potential gains in other countries. I do not account for many factors that differ across countries, including the education system, institutions and the role of parents, which could influence the effect of salt iodization policies.

Figure 8 plots the results. The dots represent the change in average standardized GPA from 1988-1998 to 2002-2006 in each municipality in the treatment and control groups, relative to a mildly iodine deficient (80 μg/liter) municipality. The solid black line in Figure 8 shows the predicted relationship between initial iodine deficiency and the increase in average GPA due to salt iodization, using a third order polynomial. The dashed line is an extrapolation from this prediction.

In line with the findings of the paper, the predicted treatment effect in Figure 8 is increasing in the severity of iodine deficiency. Moreover, because Danes were mildly to moderately iodine-deficient prior to the reforms, the treatment effects observed in the paper are small compared to the prediction for more severely deficient populations. For moderate iodine deficiency, the predicted treatment effect is 0.09 standard deviations, and in environments with severe iodine deficiency the predicted treatment effect is 0.58 standard deviations. While these predictions are not directly applicable to other countries, they suggest that the benefits of salt iodization are much larger in more deficient populations. Globally, 15.9% of school-age children are mildly iodine deficient, 8.1% are moderately iodine deficient, and 5.2% are severely iodine deficient (Andersson et al., 2012).

7 Conclusion

The worldwide adoption of iodized salt over the past three decades is one of the most successful public health interventions in recent times. The focus of these efforts has been to prevent mental retardation caused by in utero exposure to maternal iodine deficiency. While this is the most severe consequence of iodine deficiency, my analysis shows that salt iodization policies benefit a much broader group of individuals.

Using the introduction of iodized salt in Denmark over the period 1998-2001, I find that salt iodization improves cognitive performance among adolescents. I show that this effect most likely arises from the contemporaneous effect of iodine deficiency on metabolic functioning and brain activity. As iodine is crucial for the metabolism in all stages of life, this suggests that similar benefits of salt iodization may be found for adults. If so, the aggregate societal benefits of salt iodization policies would be considerably larger than previously thought.

While the use of iodized salt has reduced the incidence of iodine deficiency dramatically, about one-third of the world population remain iodine deficient (Andersson et al., 2012). Hence, there is still a large untapped economic potential in eradicating iodine deficiency. My results are especially relevant for other European countries, where iodine deficiency is not considered a serious health concern, despite the region having one of the highest rates of deficiency and the lowest rate of salt iodization (WHO, 2007). In developing countries, where severe iodine deficiency is more prevalent, my estimates add to the already large expected benefits of salt iodization.

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A Appendix

A.1 Effect of Salt Iodization on Hyperthyroidism

In this section, I estimate the effect of the Danish salt iodization policies on the incidence of hyperthyroidism. Hyperthyroidism is a condition of overactive metabolism caused by an excess of thyroid hormones, which can arise when iodine intake is increased suddenly after prolonged deficiency, for instance, as a consequence of salt iodization (Feyrer et al., 2017). I use data on hospital contacts with hyperthyroidism diagnoses from the National Hospital Register ('Landspatientregistret') during 1994-2006 and for the full population of Denmark.[38] I estimate Difference-in-Differences models as in the main analysis. I split the data into two age groups, 0-59 years and 60-100 years, because hyperthyroidism is much more common among the elderly, see Figure A.1.

Figure A.1: Incidence of Hyperthyroidism by age

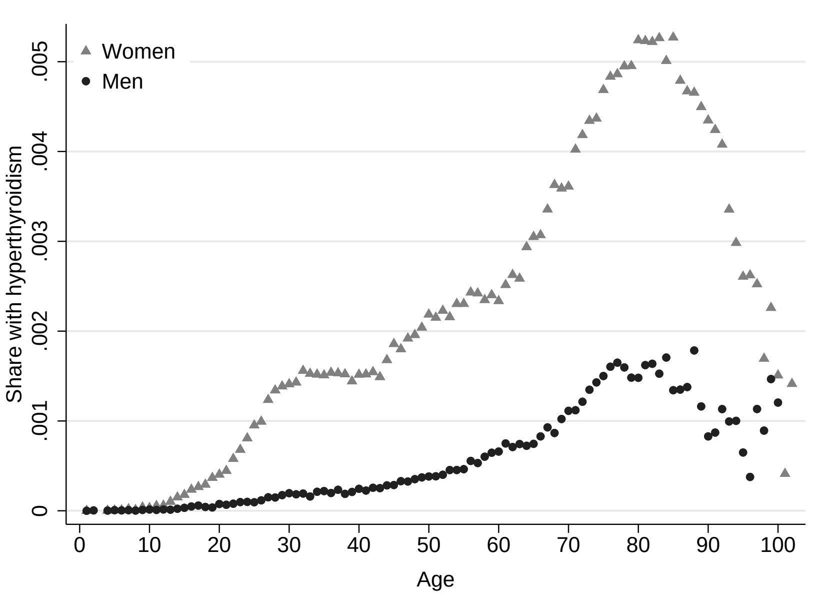
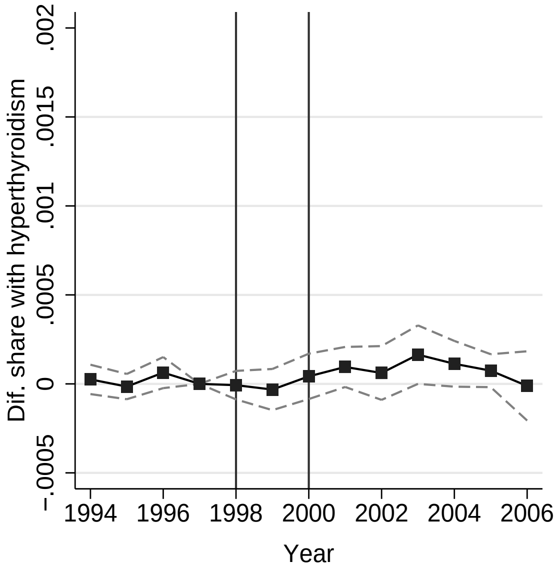


Figure A.2 shows the Difference-in-Differences results. Overall, there is little effect on the incidence of hyperthyriodism among the young while both salt iodization reforms, in 1998 and 2000/2001, cause an increase in cases among the elderly. The lack of an effect on the young

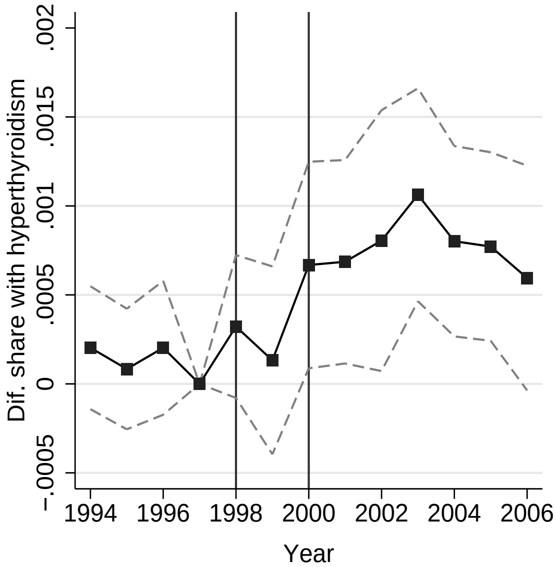
[38]The ICD-10 diagnosis code for hyperthyroidism is "E05".

may be explained by their dramatically lower baseline incidence, see Figure A.1, or that their thyroid glands are more able to adapt to the new level of iodine intake.

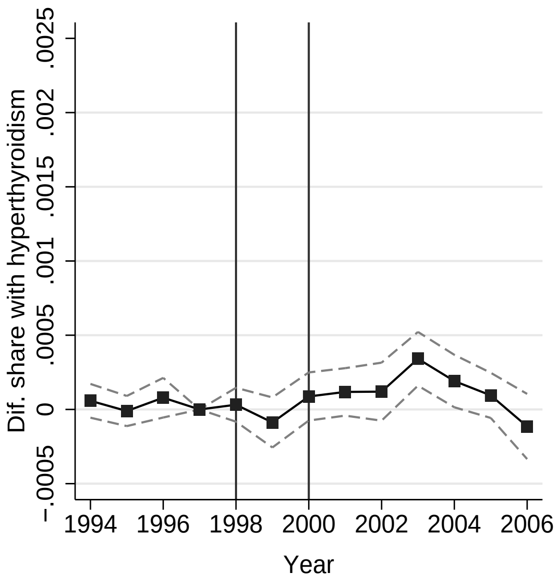
Figure A.2: Effect of Salt Iodization on Hyperthyroidism Diagnoses



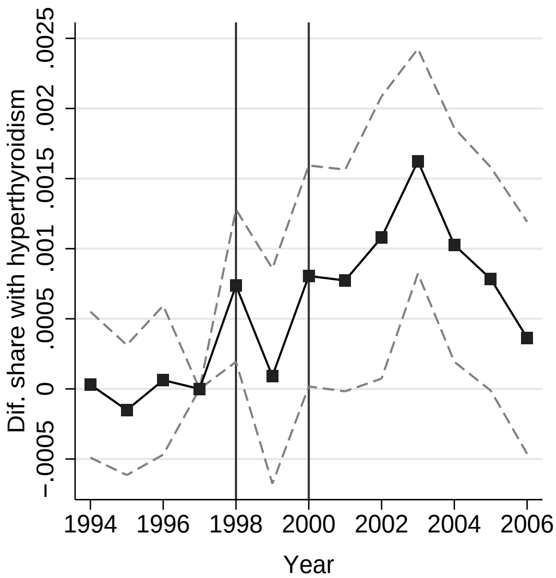
A Discrete: Ages 0-59



B Discrete: Ages 60-100



C Continuous: Ages 0-59



D Continuous: Ages 60-100

Note: The figure plots the difference in the incidence of hyperthyroidism between iodine-poor and iodine-rich areas for each year during 1994-2006, relative to the base year 1997. The dotted grey lines represent 95% confidence intervals, using standard errors clustered by municipality. The two vertical lines at year 1998 and 2000 mark the two salt iodization reforms in 1998 and 2000/2001. Panels A and B uses the discrete treatment variable and the difference between municipalities with below and above median iodine concentrations in drinking water. Panels C and D uses the continuous treatment variable, $Treat = -log(IodineConcentration)$.

These results confirm that the two salt iodization reforms increased iodine intake and that the treatment variables capture real differences in the response to the reforms. While hyperthyroidism is a negative side effect of salt iodization, the incidence among the young is too low to matter for the main analysis.

A.2 Drinking Water Data

I determine the municipality-specific iodine concentration in drinking water using groundwater analyses provided by the Geological Survey of Denmark and Greenland (GEUS). The data contain information on the iodine concentration in each sample and coordinates for where the sample was taken. I supplement this with GEUS data on all water works and wells used for private consumption along with their coordinates. I match each water work to the five nearest iodine samples to obtain a dataset containing iodine concentrations at the water-work-level. I then collapse the data at the municipality-level, using the position of the water work and weighting by their size.[39] Figure A.3 shows a map of the data on water works and iodine samples across areas of Denmark.

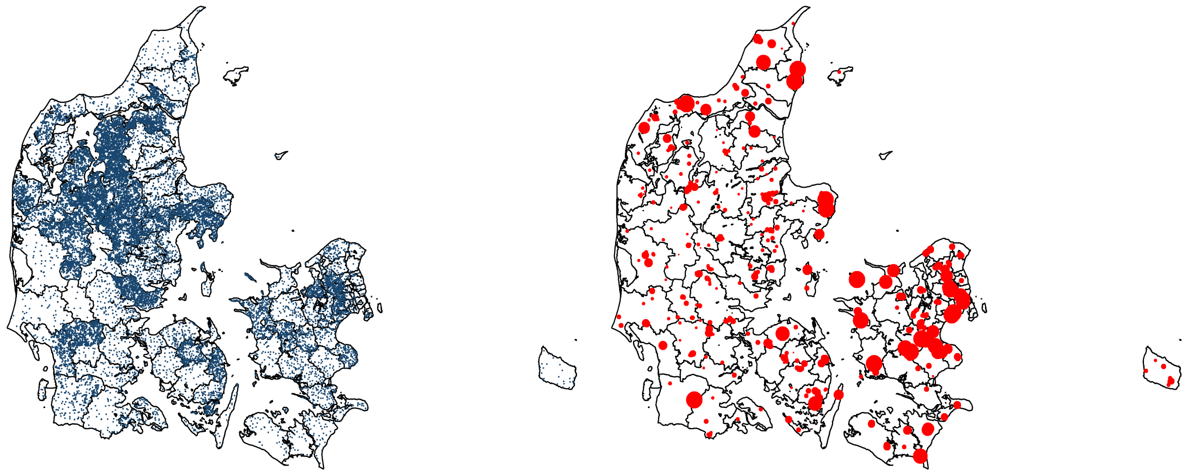
I use this approach, first creating a water-work-level dataset and then collapsing by municipality, because this accounts for the placement of water works within a municipality. Hence, if a municipality obtains all of its water from wells near the municipality border, iodine samples close to the border, including samples in the neighboring municipality, will be given a higher weight in the calculation of the municipality's average iodine concentration in drinking water.

Furthermore, I account for water supply collaborations across municipalities in the greater capital region by using official water supply plans published by the municipalities. For instance, Copenhagen municipality, the capital of Denmark, gets its drinking water from five large waterworks in the outskirts of greater Copenhagen and do not use water from local wells. Therefore,

[39]The data splits water wells into four categories: 1-2 households, 3-9 households, public water works and private water works. The first two categories are given a weight according the share of the population covered by them, that is, on average, 1.5 and 6 households per well, respectively. Public and private waterworks are given a weight based on the remaining population in the municipality with twice the weight on public water works as they are typically larger.

I use a weighted average of the iodine concentration in drinking water from these five water works rather than the iodine concentration in groundwater samples in Copenhagen.

Figure A.3: Water Wells and Iodine Samples



A Water Works and Wells | **B** Iodine Samples

Note: Panel A plots the position of water works and wells in Denmark. Panel B plots the position of iodine samples of groundwater in Denmark, where the size of the dots is proportional to the iodine concentration (ug/l) in groundwater. Data source: Geological Survey of Denmark and Greenland (GEUS).

A.3 Functional Form Assumptions

Figure A.4 plots the change in average standardized GPA from 1988-1998 to 2002-2006 against the iodine concentration in drinking water across municipalities. I include a LOWESS (Locally Weighted Scatterplot Smoothing) line to draw inferences about the functional form. Figure A.4 also plots the predictions of the two treatment variables used in the main analysis. The discrete treatment variable measures the average difference in the change in standardized GPA between individuals living in areas with above and below median iodine concentrations in drinking water. Hence, this variable does not assume a specific functional form. The continuous treatment variable, however, assumes that the change in average standardized GPAs over time is linearly related to the negative log of iodine concentrations in drinking water. Despite this strong assumption, the imposed relationship between iodine concentrations in drinking water and the change in GPA over time, based on this variable, is close to the LOWESS estimate. This suggests that the functional form of the continuous treatment variable is a good approximation of the true functional form.

In the empirical analysis, I scale the continuous treatment variable to reflect the effect of going from the 95th to the 5th percentile of iodine concentrations in drinking water. Therefore, the coefficients of the discrete and continuous treatment variables are not directly comparable. If we instead compare predicted treatment effects for individuals with below median iodine concentrations in drinking water in Figure A.4, the estimated effect of salt iodization is 0.057 and 0.056 standard deviations for the discrete and continuous treatment variables, respectively. Figure A.5 plots the distribution of the continuous treatment variable.

Figure A.4: Test of Functional Form Assumptions

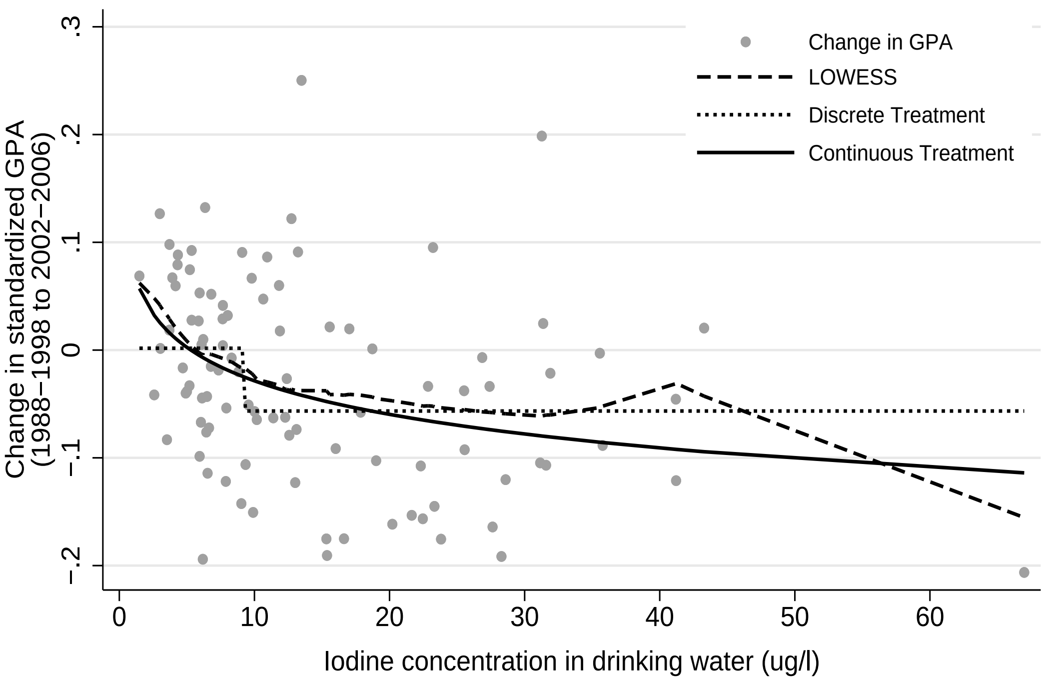
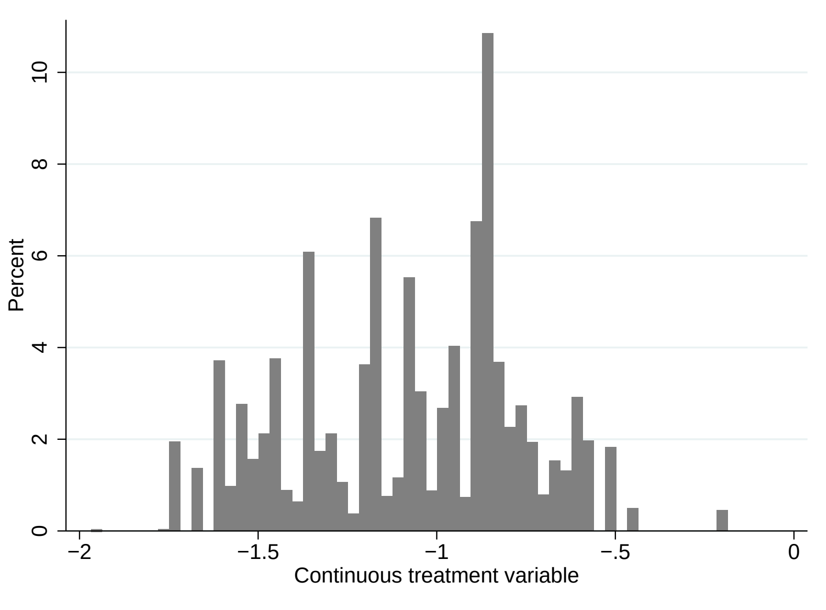


Figure A.5: Distribution of Continuous Treatment Variable



Note: The figure plots the distribution of the continuous treatment variable, $Treat = -log(IodineConcentration)$, scaled such that the distance between the 5th and 95th percentile is equal to one.

A.4 Measurement Error and Implications for Estimates

Ideally, the treatment variables would measure the counterfactual iodine intake of each student in the sample. In practice, the treatment variables are based on groundwater iodine samples collapsed at the municipality level. Therefore, the analysis is potentially subject to several types of measurement error. First, the reported iodine concentrations in groundwater are based on iodine samples that are measured with noise. Secondly, even though drinking water in Denmark is derived entirely from groundwater, the link between iodine concentrations in groundwater and drinking water may not be perfect. Third, there are other sources of iodine than drinking water, including milk, fish and vegetables.

To assess the implications of measurement error for the estimates, consider the classical errors-in-variables model:

$$y_i = \beta x_i + \epsilon_i \tag{A.1}$$

$$\tilde{x}_i = x_i + u_i \tag{A.2}$$

where x_i is the true treatment variable, $\tilde{x}_i$ is the observed treatment variable and u_i is the measurement error. The measurement error has mean zero and is uncorrelated with y, x and ϵ. The estimated β-parameter is then attenuated according to a reliability ratio:

$$\hat{\beta} = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_u^2}\beta = \frac{\sigma_x^2}{\sigma_{\tilde{x}}^2}\beta \tag{A.3}$$

where σ_x^2 is the variance of the true treatment variable, $\sigma_{\tilde{x}}^2$ is the variance of the observed treatment variable and σ_u^2 is the variance of the measurement error. Because the measurement error is unobserved, the reliability ratio is not known.

However, I can provide a guesstimate of the amount of measurement error arising from noise in groundwater samples – the first source of measurement error described above. To do this, I draw random measurement errors from municipality-specific normal distributions with mean zero and variance equal to the variance of the estimated iodine level in drinking water in the municipality.[40] I then calculate the variance of the measurement errors. Repeating this procedure 500 times and averaging across iterations, I obtain an estimate of σ_u^2. Lastly, I calculate the variance of the true treatment variable as $\sigma_x^2 = \sigma_{\tilde{x}}^2 - \sigma_u^2$. The resulting reliability ratio is 0.64, suggesting that 64 % of the variance in the measured drinking water iodine concentrations is true variation. Hence, if we believe these calculations, the true treatment effects are $\frac{1}{0.64} = 1.6$ times larger than the observed treatment effects.

Geographical Fixed Effects

In Table 3 in the Robustness Section, adding region-by-year fixed effects to the regressions leads to smaller coefficients. This may be caused by a worsening of the attenuation bias. Adding region-by-year fixed effects reduces the variance of the true treatment variable without reducing the variance of the measurement error. To assess whether a worsening of the attenuation bias can explain the observed change in coefficients in Table 3, I calculate the degree of measurement error required to produce these results. I start from the ratio of the fixed effect estimates to the

[40] I estimate this variance for each municipality by regressing the iodine level in groundwater samples on a constant, using the weight different samples are given in the calculation of the mean iodine level of that municipality.

baseline estimate, henceforth called the fixed effect ratio:

$$\frac{\hat{\beta^{FE}}}{\hat{\beta}} = \frac{\frac{\sigma^2_{x-\bar{x}}}{\sigma^2_{\tilde{x}-\bar{\tilde{x}}}}}{\frac{\sigma^2_{x}}{\sigma^2_{\tilde{x}}}} \tag{A.4}$$

If we assume measurement errors are uncorrelated within fixed effects groups, $cov(u_i, u_j) = 0$, including fixed effects only reduces true variation in the treatment variable: $\sigma^2_{\tilde{x}-\bar{\tilde{x}}} - \sigma^2_{\tilde{x}} \approx \sigma^2_{x-\bar{x}} - \sigma^2_{x}$.[41] Using these equations and defining the baseline reliability ratio as $\mu = \frac{\sigma^2_x}{\sigma^2_{\tilde{x}}}$, I get:

$$\frac{\hat{\beta^{FE}}}{\hat{\beta}} \approx \frac{\sigma^2_{\tilde{x}-\bar{\tilde{x}}} - (1-\mu)\sigma^2_{\tilde{x}}}{\sigma^2_{\tilde{x}-\bar{\tilde{x}}}\mu} \tag{A.5}$$

which specifies the fixed effect ratios as a non-linear function of the baseline reliability ratio, henceforth called the FER curve. All the remaining parameters in equation (A.5) are observed. Since the fixed effect ratios are also observed, I can back out the baseline reliability ratio:

$$\mu \approx \frac{\sigma^2_{\tilde{x}-\bar{\tilde{x}}} - \sigma^2_{\tilde{x}}}{\frac{\hat{\beta^{FE}}}{\hat{\beta}}\sigma^2_{\tilde{x}-\bar{\tilde{x}}} - \sigma^2_{\tilde{x}}} \tag{A.6}$$

Figure A.6 plots μ and equation (A.5) for the different geographical control variables used in Table 3.

If the baseline reliability ratio is equal to one, there is no measurement error and including region-by-year fixed effects should not change the estimates. For any baseline reliability ratio below one, including a West Denmark dummy attenuates parameter estimates considerably more than including one of the two degree of urbanization variables. The reason is that the West Denmark dummy takes out a larger part of the variation in the treatment variable, leaving a smaller share of true variation to identify the treatment effect. The FER curves intersect the x-axis at the point where adding the fixed effects reduces the true variance of the treatment variable to zero, at which point the fixed effects estimates are not identified. The difference in

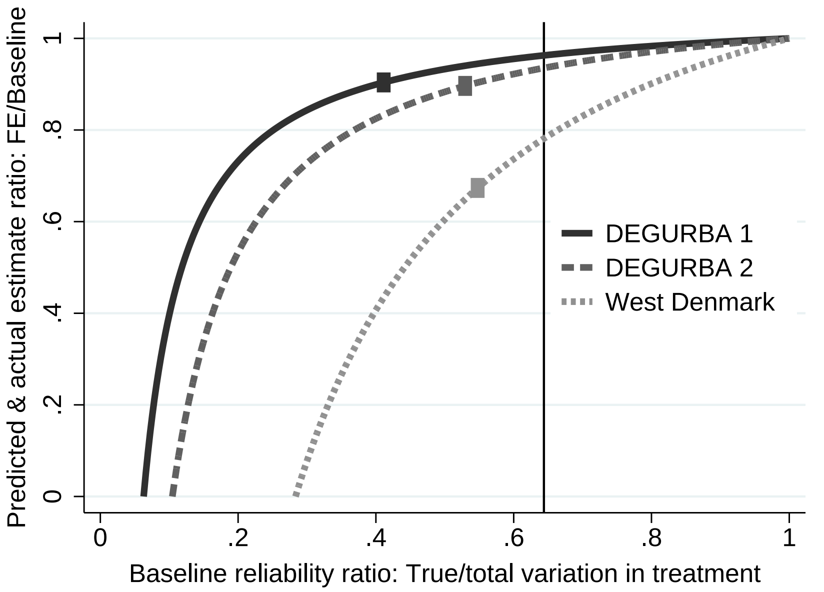
[41] This is an approximation because demeaning reduces the variance of the measurement error slightly even if $cov(u_i, u_j) = 0$:

$$\sigma^2_{\tilde{x}-\bar{\tilde{x}}} - \sigma^2_{\tilde{x}} = var(x_i - \bar{x} + u_i - \bar{u}) - var(x_i + u_i)$$
$$= var(\frac{n-1}{n}x_i - \frac{1}{n}\sum_{j\neq i} x_j + \frac{n-1}{n}u_i - \frac{1}{n}\sum_{j\neq i} u_j) - var(x_i + u_i) = -\frac{1}{n}\sigma^2_x - \frac{1}{n}\sigma^2_u - 2 \times \frac{(n-1)^2}{n^2}\sigma_{x_i,x_j}$$
$$\Leftrightarrow \sigma^2_{\tilde{x}-\bar{\tilde{x}}} - \sigma^2_{\tilde{x}} - (\sigma^2_{x-\bar{x}} - \sigma^2_x) = -\frac{1}{n}\sigma^2_u \approx 0$$

For large n (many municipalities within region-by-year fixed effect groups) $\frac{1}{n}\sigma^2_u$ is small.

these points across FER curves reflects that the West Denmark dummy takes out more variation than the degree of urbanization controls and, therefore, the minimum level of baseline true variation needed to identify the fixed effects estimates is larger. If the estimates from different models yield the same predicted baseline reliability ratio, I can attribute all of the observed change in estimates from including region-by-year fixed effects to measurement error.

Figure A.6: Measurement Error and Fixed Effects Estimates



Note: The figure shows theoretical relationships between the baseline reliability ratio and the ratio between baseline OLS estimates and fixed effects estimates for three different sets of geographical fixed effects: 1) DEGURBA 1, 2) DEGURBA 2, 3) West Denmark dummy. The points show the actual ratio between baseline OLS estimates and fixed effects estimates, provided in Table 3, for the three different sets of geographical fixed effects estimates. The DEGURBA classification by Eurostat splits municipalities into three categories; (1) densely populated areas, (2) intermediate density areas and (3) thinly populated areas, `http://ec.europa.eu/eurostat/ramon/miscellaneous/index.cfm?TargetUrl=DSP_DEGURBA`. The extended DEGURBA classification by Statistics Denmark, splits intermediate density areas and thinly populated areas in Eurostat's classification into five groups based on the number of inhabitants – a total of six degrees of urbanization. West Denmark is defined as Jutland and Funen. The vertical line represents a ballpark estimate of the level of measurement error in the data, derived in the previous section.

Empirically, the predicted baseline reliability ratios are between 0.4 and 0.55. Discrepancies across estimates may arise because geographical controls removes spurious regional shocks influencing the outcomes or because the estimated parameters are estimated with noise. To provide a conservative guesstimate of the importance of measurement error, I assume there is no noise in the estimates and that the actual baseline reliability ratio is 0.64 – the ballpark estimate provided above. Even in this case, more than half of the reduction in the treatment effects from including region-by-year fixed effects in Table 3 can be attributed to measurement error.[42]

A.5 In Utero Exposure to Salt Iodization in Denmark

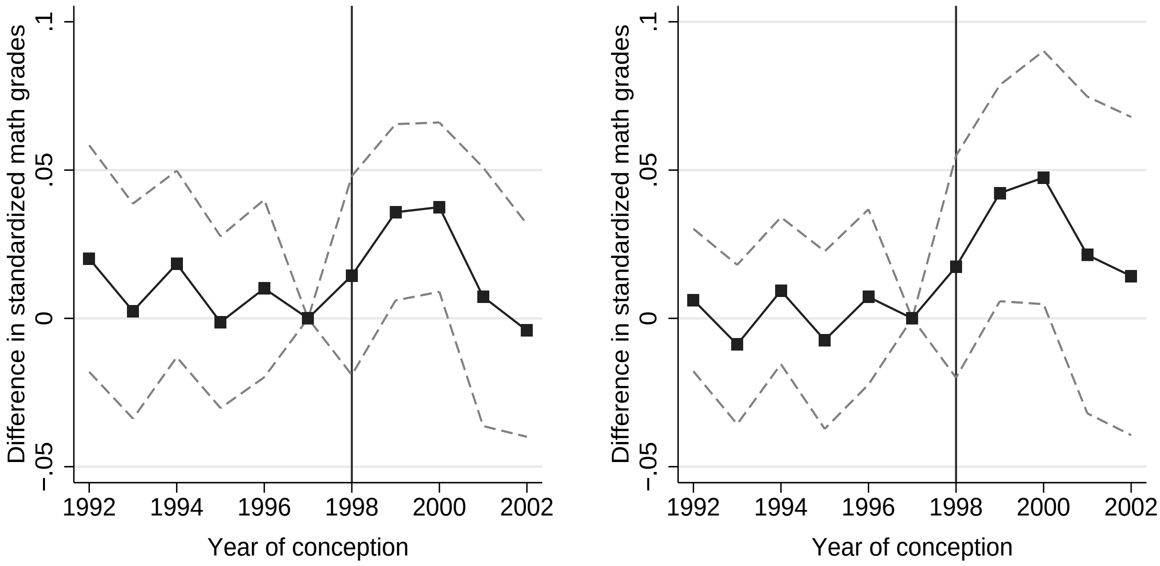
In this section, I replicate previous results on the effects of in utero exposure to salt iodization. Children exposed to the introduction of iodized salt in Denmark during 1998-2001 are now young adults. Therefore, I can use their lower/middle secondary school grades as a measure of cognitive performance. As the first salt iodization reform was introduced in June 1998, children conceived more than nine months prior, before October 1997, were not exposed in utero, while children conceived after this point were. Therefore, I can estimate Difference-in-Differences models similar to the baseline regressions, using year of conception rather than year of graduation. In these regressions, I define the pre-reform period as 1992-1997 and the post-reform period as 1998-2002.[43] For simplicity, I do not split the effects of the first and second salt iodization reform.

Figure A.7 illustrates the results on math grades, defining children as treated if they were conceived in a municipality with iodine concentrations in drinking water below the tenth percentile. Panel A shows the estimates without the inclusion of controls. The difference between the treatment and control group is on a negative trend during the pre-reform period. This may cause a negative bias in the Difference-in-Differences estimates. To deal with this issue, I estimate and take out municipality-specific linear pre-trends and use the residuals from this regression as the outcome. Since the estimates are based on a two-step procedure, I bootstrap standard errors. Panel B shows the results. Once pre-trends are accounted for, it is clear that salt iodization increases math grades, with an increase in the difference between treated and control individuals from 1998 and onwards.

[42] I get to this estimate by comparing actual fixed effects ratios across models with predicted fixed effects ratios based on a baseline reliability ratio of 0.64. The predicted fixed effects ratios are determined by the intersection between FER curves and the vertical line at 0.64 in Figure A.6.

[43] I use data on lower/middle secondary school grades from children graduating during 2008-2020, during which the same grading scale is used. The children graduate at the age of 15-17 years, which means the children in the sample were conceived between 1992-2002.

Figure A.7: Effect of In Utero Exposure to Salt Iodization on Lower/Middle Secondary School Math Grades



A Raw **B** Detrended

Table A.1 reports the results for various outcomes and definitions of treatment, using detrended outcomes as in Panel B of Figure A.7. Overall, the results suggest that even in a rich country in modern times in utero exposure to salt iodization improves cognitive ability. Math grades increase by 0.026 % of a standard deviation when using the continuous treatment variable. This increase is driven by improvements in areas with iodine concentrations in drinking water below the tenth percentile. Danish grades actually decrease in response to salt iodization. However, this decrease occurs after 2001. Birthweight increases slightly, by 18 grams (0.6 %), which may suggest a small improvement in fetal health.

Compared to previous studies, the effect of in utero exposure to salt iodization in Denmark is relatively small. One likely explanation is that previous studies either estimate the effect of recent reforms in developing countries or historical reforms in industrialized countries, where the degree of iodine deficiency is much more severe than in Denmark in 1998. Deng and Lindeboom (2019) estimate the effect of salt iodization in China in 1994 on math test scores among school-age children – a potentially comparable outcome to math grades of lower/middle school graduates in Denmark. They find that a one standard deviation increase in goiter rates (12

%-points) is associated with an 9 % larger increase in math test scores following salt iodization. If we apply these estimates to the degree of iodine deficiency present in Denmark before the reforms, salt iodization is expected to increase math grades by 2.3 percent.[44] The actual change in column two of Table A.1 is 1.1 percent.

Table A.1: Effects of In Utero Exposure to Salt Iodization

	Continuous	Iodine Drinking Water < P10	Iodine Drinking Water < P50
Math Grades	0.026	0.028	0.007
	(0.019)	(0.018)	(0.013)
Danish Grades	-0.009	-0.018	-0.009
	(0.022)	(0.026)	(0.013)
Birthweight	18.5	12.0	7.2
	(12.3)	(15.9)	(8.5)
Observations	653,892	653,892	653,892

Note: The estimates reflect the change in standardized average lower/middle school grades and average birth weights of children conceived in iodine-poor vs. iodine-rich areas from 1992-1997 to 1998-2002. I detrend outcomes by calculating residuals from regressions with municipality-specific pre-trends. To account for the two-step estimation, standard errors are bootstrapped with 500 repetitions and clustered sampling at the municipality level. Column 1 shows the results for the continuous treatment variable, column 2 shows the results using a treatment variable equal to one for individuals in municipalities with iodine concentrations below the tenth percentile, and column 3 shows the results using a treatment variable equal to one for individuals in municipalities with iodine concentrations below the median. *** p<0.001 ** p<0.05, * p<0.1.

The effects of in utero exposure are also surprisingly small compared to the effects of exposure to salt iodization in adolescence presented throughout this paper. This may be explained by differences in the use of vitamin and mineral supplements. Around 46 percent of 18-22-year-old women used vitamin and/or mineral tablets before the salt iodization reforms were introduced (Knudsen et al., 2002). In comparison, 93 % of pregnancy women used vitamin and/or mineral tablets (Nøhr et al., 1993). Hence, the smaller effect of in utero exposure to salt iodization may arise because pregnant women were, on average, significantly less deficient than high school students before the reforms.

[44] I create this back-of-the-envelope calculation by converting iodine concentrations in drinking water into goiter rates, which are not observed in the data. I do this by first converting to median urinary iodine concentrations using Pedersen et al. (1999): $IodineUrine = 43.2 + 1.7 \times IodineWater$. I then convert these to goiter rates using estimates from Liu et al. (2010), Fig. 4A. Based on these calculations, the predicted pre-iodization goiter rate in Denmark ranges from 4.3 to 7.4 %. This difference is around 25 % of a standard deviation of the goiter rate distribution in Deng and Lindeboom (2019).

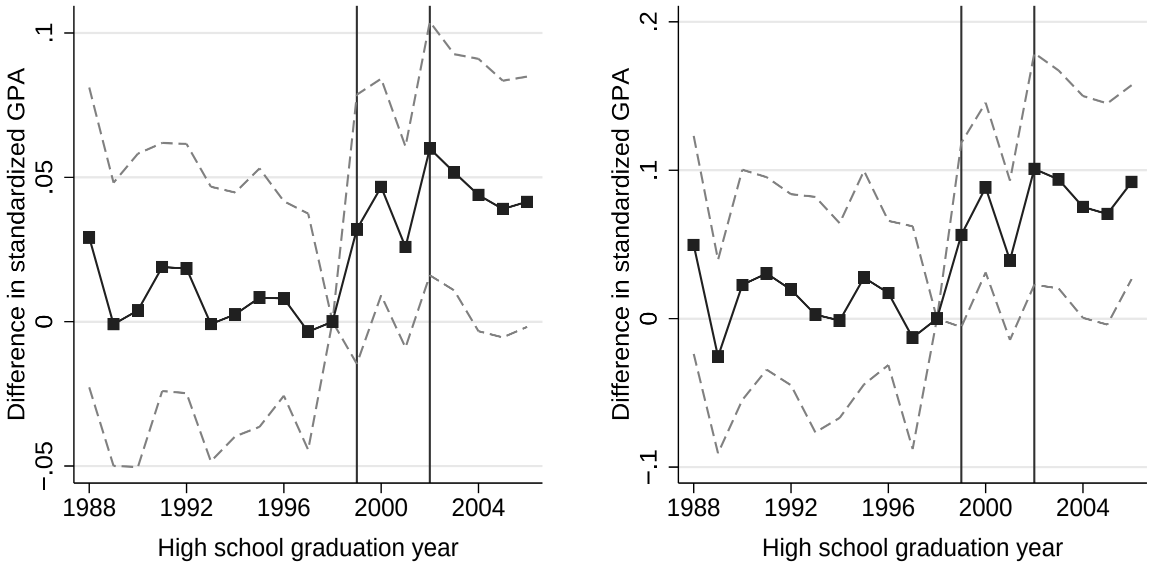
A.6 Additional Tables and Figures

Table A.2: The Effect of Salt Iodization By Gender

	Discrete			Continuous		
	Baseline	Men	Women	Baseline	Men	Women
First Reform	0.039***	0.050**	0.030**	0.070***	0.092***	0.054**
	(0.012)	(0.022)	(0.015)	(0.017)	(0.030)	(0.023)
Second Reform	0.057***	0.043**	0.062***	0.094***	0.073**	0.101***
	(0.013)	(0.020)	(0.013)	(0.020)	(0.032)	(0.022)
Observations	308,718	122,433	186,285	308,718	122,433	186,285
P-value, dif.		0.344			0.415	
R^2	0.120	0.113	0.131	0.120	0.113	0.131

Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). Columns 1 and 4 present baseline estimates pooling women and men. Columns 2, 3, 5, and 6 show separate results for men and women. Columns 1-3 show the results for the discrete treatment variable, columns 4-6 show the results for the continuous treatment variable. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. All control variables are included as dummies. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

Figure A.8: Difference in Average Grade Point Averages Across Iodine-Poor and Iodine-Rich Areas Over Time Without Control Variables



A Discrete

B Continuous

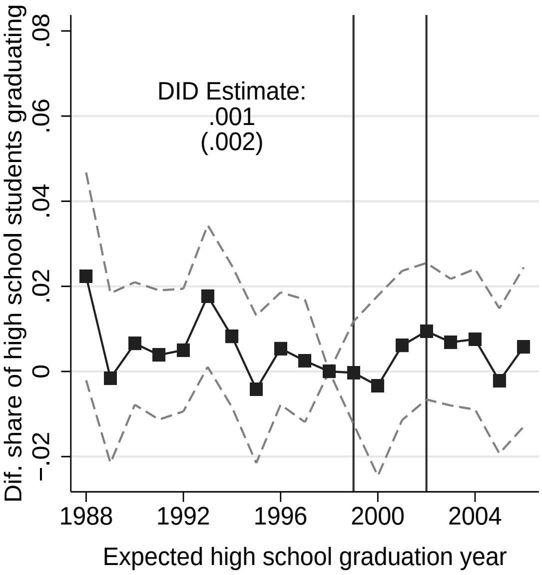
Note: The figure plots the difference in average standardized GPA between iodine-poor and iodine-rich areas for each year during 1988-2006, relative to the base year 1998. The dotted grey lines represent 95% confidence intervals, using standard errors clustered by municipality. Panel A shows the results for the discrete treatment measure, panel B shows the results for the continuous treatment measure. No control variables are included in the regressions. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization.

Table A.3: The Effect of Salt Iodization on the Grade Point Averages of STX and HF Students

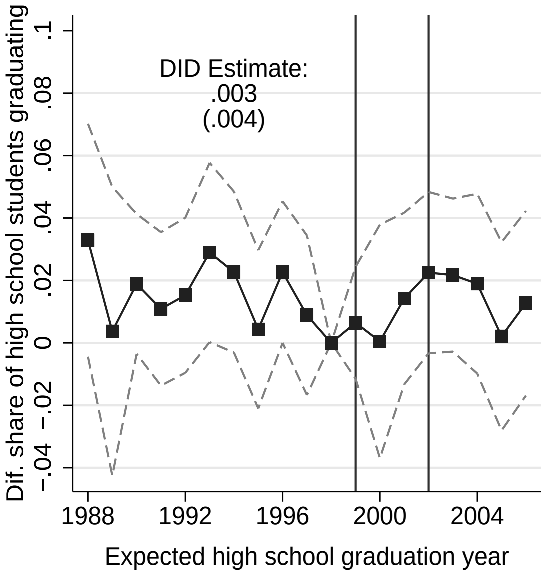
	Discrete		Continuous	
	Baseline	Including HF	Baseline	Including HF
First Reform	0.039***	0.032***	0.070***	0.057***
	(0.012)	(0.011)	(0.017)	(0.017)
Second Reform	0.057***	0.052***	0.094***	0.088***
	(0.013)	(0.013)	(0.020)	(0.019)
Observations	308,718	461,801	308,718	461,801
R^2	0.120	0.102	0.120	0.102

Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). Columns 1 and 3 present baseline estimates on STX students. Columns 2 and 4 show results on the pooled sample of STX and HF students. Columns 1-2 show the results for the discrete treatment variable, columns 3-4 show the results for the continuous treatment variable. The following set of controls is used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order, municipality and high school institution fixed effects. High school institution fixed effects are included to account for differences between STX and HF schools. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

Figure A.9: The Effect of Salt Iodization on the Probability of Graduating High School



A Discrete



B Continuous

Note: The figure plots the difference in the share of high school students who graduate between iodine-poor and iodine-rich areas for each year during 1988-2006, relative to the base year 1998. The regressions include municipality fixed effects. The dotted grey lines represent 95% confidence intervals, using standard errors clustered by municipality. Panel A shows the results for the discrete treatment measure, panel B shows the results for the continuous treatment measure. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization.

Table A.4: Robustness to Extra Control Variables

	(1)	(2)	(3)	(4)	(5)
First Reform	0.070***	0.069***	0.069***	0.068***	0.068***
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)
Second Reform	0.094***	0.094***	0.094***	0.090***	0.091***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Baseline	X	X	X	X	X
Labor Market		X	X	X	X
Family			X	X	X
Birth					X
Observations	308,718	308,718	308,718	181,745	181,745
R^2	0.120	0.120	0.121	0.134	0.134

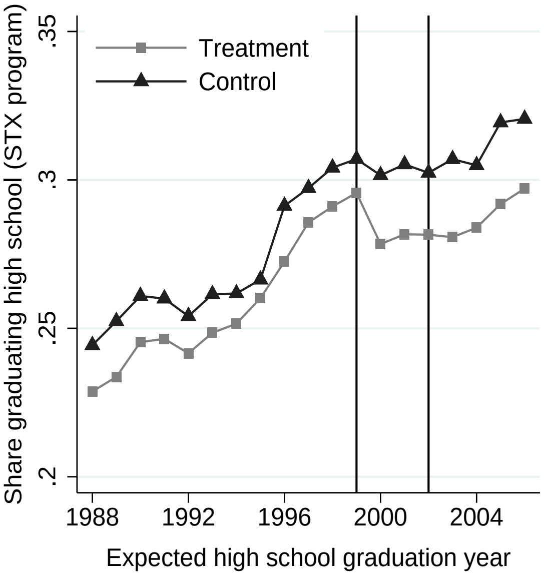
Note: The estimates reflect the differential change in the standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row), using the continuous treatment variable. Baseline controls: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. Labor market controls: Dummies for whether the parent is unemployed, retired, on disability pension, on temporary leave, or not in the work force for other reasons. Family controls: Dummies for whether parents are married to each other, number of living parents, and whether the student lives with a parent. Birth controls: Birth weight and birth length dummies. Because of data availability, columns 4 and 5 are based on a restricted sample: Years 1995-2006 and student age below 22. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

Table A.5: Robustness to Including Family Fixed Effects

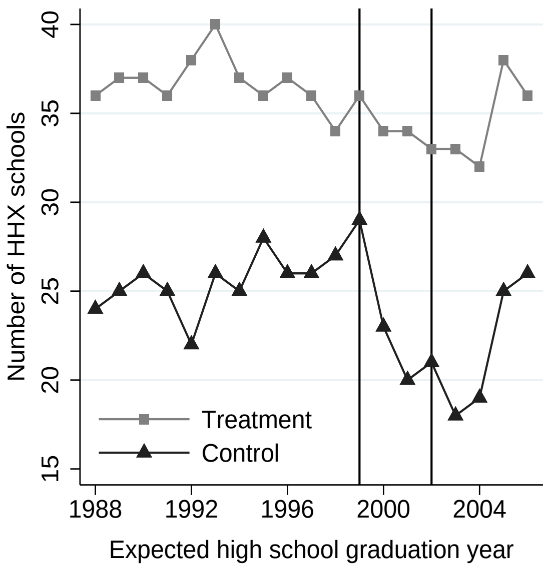
	Discrete			Continuous		
	(1)	(2)	(3)	(1)	(2)	(3)
First Reform	0.039***	0.042***	0.038	0.070***	0.060**	0.043
	(0.012)	(0.014)	(0.024)	(0.017)	(0.023)	(0.038)
Second Reform	0.057***	0.055***	0.044	0.094***	0.078***	0.029
	(0.013)	(0.020)	(0.034)	(0.020)	(0.029)	(0.055)
Baseline	X	X	X	X	X	X
Family Fixed Effects			X			X
Observations	308,718	127,456	127,456	308,718	127,456	127,456
P-value: Dif: 1st ref.		0.792			0.478	
P-value: Dif: 2nd ref.		0.608			0.174	
R^2	0.120	0.115	0.672	0.120	0.115	0.672

Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). Columns 1, 4 present baseline estimates using the following controls: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order, municipality fixed effects. Columns 2 and 4 shows baseline estimates on a subsample of students with siblings who are also high school graduates. Columns 3 and 6 add family fixed effects. Columns 1-3 show the results for the discrete treatment variable, columns 4-6 show the results for the continuous treatment variable. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

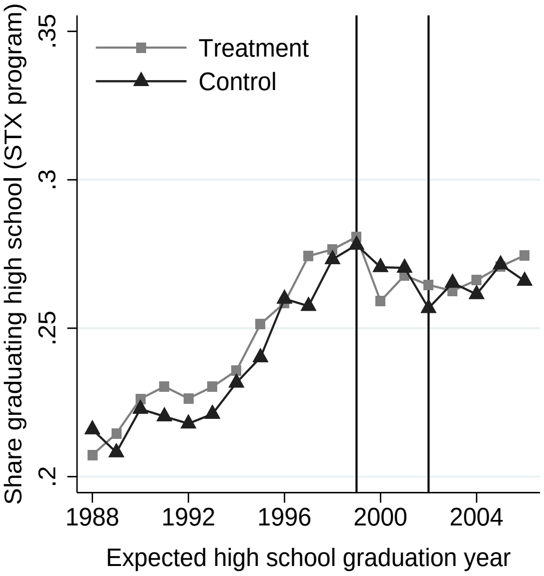
Figure A.10: Explanation for Differential Change in Graduation Rates in 2000



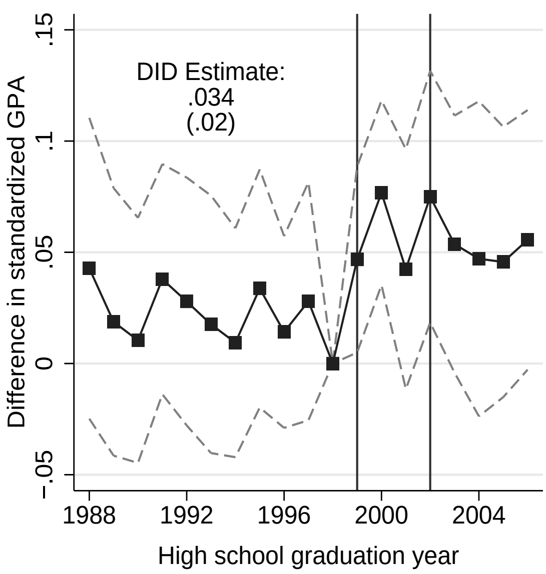
A Sample Selection



B Number of HHX Schools Over Time



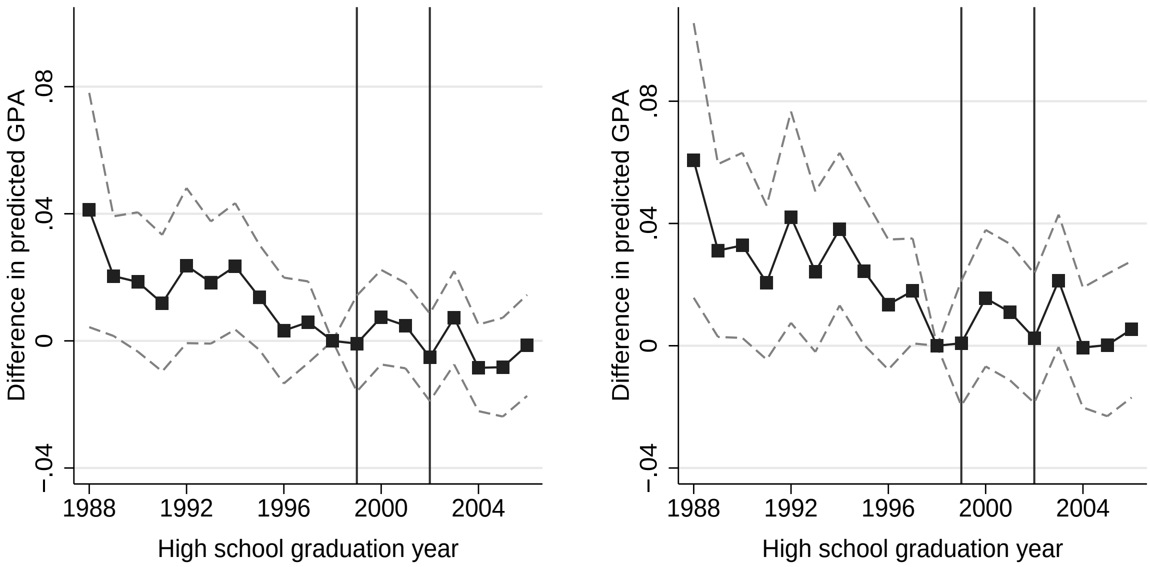
C Sample Selection, No School Closure Sample



D Effect on GPA, No School Closure Sample

Note: Panel A reports the share of lower/middle secondary school graduates in treatment and control group municipalities, defined using the discrete treatment variable, that graduate from an STX high school education. I plot this for each expected high school graduation year (three years after leaving lower/middle secondary school) during 1988-2006. Panel B shows the number of HHX high schools in treatment and control group municipalities over time. A HHX school is defined as an institution in which 20 or more students start a HHX program in a given year. To match the other graphs, the number of HHX schools is plotted against the expected graduation year of the students, which is three years after enrollment. Panel C plots the share of lower/middle secondary school graduates in treatment and control group municipalities that graduate from high school, excluding municpalities where at least two students have historically attended a HHX school that closed in 1996 or 1997 (affecting graduation rates in 1999 and 2000). This restriction drops about 20 percent of the municipalities and 40 percent of the STX graduates from the sample. Panel D shows the baseline results on grades using this restricted sample. Standard errors clustered by municipality are shown in parentheses. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization.

Figure A.11: Difference in Average Predicted GPA Across Iodine-Poor and Iodine-Rich Areas Over Time



A Discrete

B Continuous

Note: The figure plots the difference in average predicted GPA between iodine-poor and iodine-rich areas for each year during 1988-2006, relative to the base year 1998. The prediction of GPA is based on the full set of control variables: Parents: Income percentile, years of schooling, labor market controls, familiy controls, age. Students: Age, birth year, gender, number of siblings and birth order. Labor market controls: Dummies for whether the parent is unemployed, retired, on disability pension, on temporary leave, or not in the work force for other reasons. Family controls: Dummies for whether parents are married to each other, number of living parents, and whether the student lives with a parent. The dotted grey lines represent 95% confidence intervals, using standard errors clustered by municipality. Panel A shows the results for the discrete treatment measure, panel B shows the results for the continuous treatment measure. The vertical lines at 1999 and 2002 mark the introduction of voluntary and mandatory salt iodization.

Table A.6: Robustness to Controlling for Pre-Reform Program Shares by Year

	Discrete		Continuous	
	Baseline	Incl. Program Shares	Baseline	Incl. Program Shares
First Reform	0.039***	0.030***	0.070***	0.062***
	(0.012)	(0.011)	(0.017)	(0.016)
Second Reform	0.057***	0.046***	0.094***	0.082***
	(0.013)	(0.013)	(0.020)	(0.020)
Observations	308,718	308,718	308,718	308,718
R^2	0.120	0.120	0.120	0.120

Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). Columns 1 and 3 present baseline estimates using the following controls: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order, municipality fixed effects. Columns 2 and 4 add controls for the average within-municipality share of lower/middle secondary school graduates that enroll in the STX, HTX, HHX and HF high school programs during the pre-reform period 1988-1998 interacted with graduation year dummies. Columns 1-2 show the results for the discrete treatment variable, columns 3-4 show the results for the continuous treatment variable. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

Table A.7: Robustness of Main Results to Choice of Standard Errors

	Baseline: by Muni.	By School	By Muni#School	By Province
First Reform	0.070***	0.070***	0.070***	0.070***
	(0.000125)	(0.000219)	(0.000209)	(0.000384)
Second Reform	0.094***	0.094***	0.094***	0.094***
	(0.000006)	(0.000008)	(0.000024)	(0.000100)

Note: p-values are reported in parentheses. Column 1 shows baseline results using standard errors clustered by municipality. Column 2 show results with standard errors clustered by high school institution. Column 3 show results with twoway-clustered standard errors by municipality and high school institution. Column 4 show results with standard errors clusterred by province, which are 11 large geographical areas. Due to the small number of clusters, these standard errors are estimated using a wild bootstrap procedure proposed by Cameron et al. (2008). The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row). The regressions include the following control variables: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order, municipality fixed effects. All control variables are included as dummies. *** p<0.001 ** p<0.05, * p<0.1.

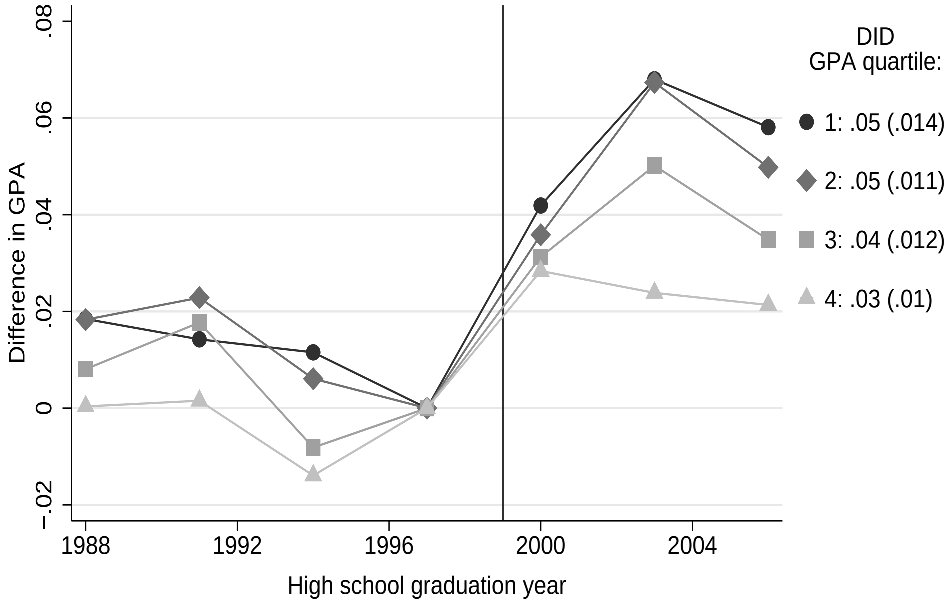
A.7 Figures and Tables Using the Discrete Treatment Variable

Table A.8: Robustness to Geographical Control Variables

	(1)	(2)	(3)	(4)
First Reform	0.039***	0.038***	0.037***	0.025*
	(0.012)	(0.012)	(0.012)	(0.013)
Second Reform	0.057***	0.052***	0.051***	0.038**
	(0.013)	(0.013)	(0.013)	(0.016)
Baseline	X	X	X	X
DEGURBA 1		X		
DEGURBA 2			X	
West Denmark				X
Observations	308,718	308,718	308,718	308,718
R^2	0.120	0.120	0.120	0.120
P-value, dif. 1st reform		0.846	0.614	0.055
P-value, dif. 2nd reform		0.292	0.268	0.037
R^2 of Treat		0.032	0.049	0.241

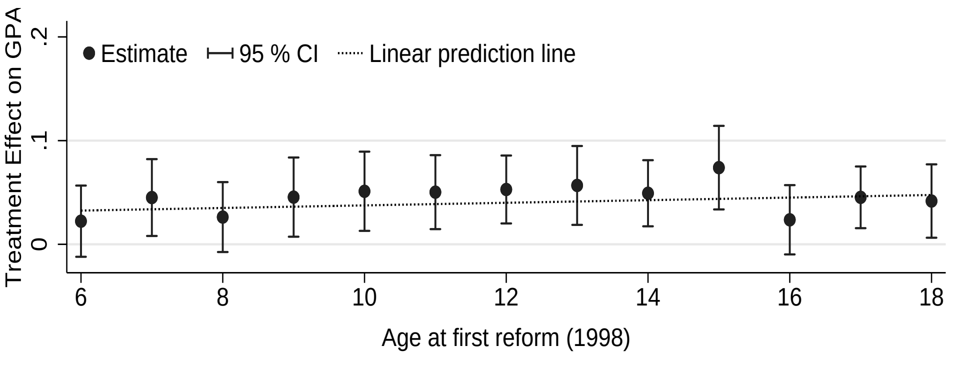
Note: The estimates reflect the differential change in standardized GPA of high school students in iodine-poor vs. iodine-rich areas from 1988-1998 to 1999-2001 (first row) and 2002-2006 (second row), using the discrete treatment variable. Baseline controls: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects. DEGURBA 1: Dummies for the three categories in Eurostat's DEGURBA classification interacted with graduation year dummies. DEGURBA 2: Dummies for the five categories in Statistics Denmark's extended DEGURBA classification interacted with graduation year dummies. West Denmark: Dummy for living in Jutland or Funen (West Denmark) interacted with graduation year dummies. Standard errors clustered by municipality are reported in parentheses. *** p<0.001 ** p<0.05, * p<0.1.

Figure A.12: Effect of Salt Iodization on Different Quartiles of Grade Point Averages



Note: The figure shows the difference in the first, second, third and fourth quartiles of GPA across iodine-poor and iodine-rich areas during the period 1988-2006, using the discrete treatment variable. The coefficients are estimated with quantile regression using the Jittering method with 1,000 repetitions (Machado and Santos Silva, 2005). Years are pooled in groups of three; e.g., the coefficient in 1991 is based on the years 1990,1991, and 1992. Estimates are relative to the baseline level in 1997. Difference-in-Differences estimates are reported to the right. These reflect the effect of salt iodization on each GPA quartile. No control variables are included in the regressions. Misspecification-robust standard errors are reported in parentheses. Cluster-robust standard errors have not been developed for the Jittering method. If I instead estimate the coefficients using just one repetition and standard quantile regression with standard errors clustered by municipality, the estimates and standard errors are: 0.06 (0.016), 0.04 (0.015), 0.05 (0.015), 0.03 (0.017) from the first to fourth quartile of grades.

Figure A.13: Treatment Effects by Age at Introduction of Iodized Salt



Slope of Prediction Line and Tests of the Mechanisms

Intercept	Slope	Test 1 (slope=0)	Test 2 (intercept=slope)
0.0476	-0.0013	0.3840	0.0012
(0.0139)	(0.0014)		

Note: The figure plots estimates of the effect of salt iodization on the standardized high school GPA of students first affected by iodized salt at the ages 6-18, using the discrete treatment variable. Each point is a separate Difference-in-Differences estimate for students who graduated in the post-reform years 1999-2011. Students who graduated in 1999-2011 were, on average, 18-6 years old when the first salt fortification reform was implemented in 1998. Hence, the coefficient for age 6 (age 18) in the figure is the Difference-in-Differences estimate for students who graduated in 2011 (1999). The table reports estimates of the slope and intercept of a linear regression going from age 18 to age 6. The intercept is the estimated treatment effect for students first treated at age 18, and the slope is the effect of an additional year of exposure to salt iodization during childhood. Columns 3 and 4 report the p-value of a t-test for whether the slope is different from zero and the p-values of an F-test for whether intercept is equal to the slope. Standard errors are clustered by municipality. Baseline controls are used: Parents: Income percentile, years of schooling, age. Students: Age, birth year, gender, number of siblings, birth order and municipality fixed effects.