The Cognitive Meltdown? Radiation and Human Capital after Birth

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Abstract:
We examine the long-run effect of post-natal exposure to radiation from the Chernobyl accident on cognitive performance. To identify a causal effect, we exploit unexpected rainfall patterns in a critical time window after the disaster, which determine local fallout but have no plausible direct effect on test scores. Based on geo-coded survey data from Germany, we show that people exposed to higher radiation perform significantly worse in standardized cognitive tests 25 years later. A one-standard deviation higher exposure reduces cognitive test scores by 4.7-7.6% of a standard deviation, which is equivalent to 0.7-1.1 IQ points.
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Declaration of Interest

Declarations of interest: none

1 Introduction

A vast body of research documents the importance of the environment for the development of human capital. Exposure to pollutants such as particulate matter, lead or radiation has been shown to have lasting adverse effects on health, earnings and well-being (Almond and Currie, 2011; Graff Zivin and Neidell, 2013; Bharadwaj et al., 2017; Almond et al., 2018; Aizer et al., 2018). But although the existing evidence is compelling, it is largely based on exposure during pregnancy and early childhood, a period during which the human body is particularly vulnerable. In contrast, there is scant evidence about the long-run impact of pollution at later stages of the life cycle. Knowledge about the effects among adolescents and adults is critical for policymakers, as these groups form the majority of the population and may require different protective measures than small children.

In this paper, we provide evidence of long-term effects for one such environmental factor – radiation – among people who were first exposed as children, adolescents and adults. To do so, we use regional variation in radiation levels across Germany resulting from the Chernobyl accident in 1986 and estimate the effect of radiation exposure on cogintive test scores 25 years later. Due to the long half-life of the radioactive matter, people in areas with higher initial fallout have been exposed to higher radiation levels for over 30 years. For people exposed after birth, there are two plausible biological channels through which radiation can affect cognitive test scores. Medical research has shown that radiation exposure can directly affect cognition through the damage of brain cells. In addition, radiation exposure can lead to health problems, which may indirectly affect test scores.

Our dataset – the National Educational Panel Study (NEPS), a representative geo-coded survey – allows us to link fine-grained data on fallout levels in a person's municipality of residence between 1986 and 2010 to a battery of standardized cognitive tests done 25 years after the disaster. At the time of the disaster, over half of our sample were adolescents or adults, allowing us to estimate the long-run effect of exposure at these ages.

The central identification challenge is that the local level of fallout may be correlated with unobserved determinants of cognitive skills. Local fallout is determined by many factors such as rainfall, wind, and topography, some of which may be correlated with residential sorting. For example, if people with higher ability tend to live in places with less rainfall, and areas with less rainfall receive less fallout, we would obtain a spurious negative relationship between fallout and test scores. Unlike studies on early childhood exposure, we cannot exploit critical periods and hold local factors constant in a difference-in-differences setting. Every person in our sample was exposed to the same shock at the same time, which is why our identification relies on cross-sectional variation in the

intensity of the shock.

To identify a causal effect we pursue an instrumental variable strategy that isolates two determinants of local fallout that are plausibly orthogonal to residential sorting or other determinants of ability. One is the unexpected amount of rainfall in a municipality in a critical window of ten days after the disaster, while the plume was over Germany. We isolate the *unexpected* rainfall level in late April/early May 1986 by controlling for the *expected* level of rainfall – the average on the same days in a typical year. To improve the predictive power of the instrument, we interact the amount of rainfall in early May 1986 with a second source of exogenous variation, namely the amount of available radioactive matter within the plume. The amount of radioactive matter gradually decreased as the plume was moving across Germany, such that the same amount of rainfall led to higher radiation in the south east where the plume entered the country than in the north west, where it eventually vanished.

We argue that this instrument is both relevant and valid. Our first-stage regression shows that the instrument is a significant predictor for fallout. Moreover, we supply plausible arguments as well as supporting evidence in favor of both identifying assumptions, namely conditional independence and the exclusion restriction. Conditional independence is supported by balancing tests, which show that the instrument is uncorrelated with a large number of individual characteristics. We argue that the exclusion restriction is plausible because i) the instrument exploits variation in excess rainfall rather the actual level of rainfall and ii) we focus on a narrow time window of ten days after the disaster. We view it as unlikely and implausible that the deviation in rainfall from its usual level within a ten-day time window would systematically affect cognitive skills 25 years later through a different channel than radiation. We corroborate the exclusion restriction with placebo tests based on the reduced form. The instrument only has a significant effect on cognitive test scores when we use rainfall in early May 1986 but not when we use rainfall on the same days in other years.

Our central finding is that people exposed to higher levels of radiation from 1986 onward performed significantly worse in cognitive tests 25 years later. A one-standard-deviation higher initial exposure in 1986 reduces test scores by between 4.7 and 7.6% of a standard deviation. Scaled to a standard IQ measure (mean 100, sd 15), this is equivalent to a reduction by 0.7-1.1 IQ points. These results are an order of magnitude smaller than those found in in-utero studies by Almond et al. (2009) and Black et al. (2019), which is unsurprising given that radiation has a much stronger effect on a fetus than a child or an adult. Nonetheless, our results show that negative effects at later stages of life are present and non-trivial.

With this paper, we contribute to two strands of literature. First, our findings con-

tribute to the literature on the effect of pollution on human capital. This literature has produced compelling results for exposure at all ages, albeit for different types of effects. One strand of this literature focuses on exposure during pregnancy or early childhood and documents adverse long-term effects of pollution. Another strand focuses on adults and estimates the short-run effect of fluctuations in pollution on outcomes such as productivity, test scores and well-being.[1] Our study, in contrast, examines the *long-run effects* among people exposed *after early childhood*. These effects are important, not least because of the number of people affected. The cohorts in our sample represent around 24 million people, compared to 200,000 children who were in the womb at the time of Chernobyl. Even if the individual effect is smaller for people exposed after early childhood, our study shows that the environment can have adverse consequences for large parts of the population and, therefore, exposure after early childhood deserves more attention in the literature.

Second, this paper contributes to the broader literature on the effects of low-dose radiation. Two recent reviews of the epidemiological literature by Pasqual et al. (2020) and Collett et al. (2020) conclude that there is significant evidence that exposure to low-dose radiation early in life has negative effects on health and cognitive performance. For example, significant negative effects of early-life exposure on test scores and earnings have been documented for the Chernobyl accident (Almond et al., 2009; Heiervang et al., 2010; Yemelyanau et al., 2012) and exposure to fallout from Soviet nuclear testing (Black et al., 2019). However, the aforementioned reviews find few studies on the causal effect of exposure to low-dose radiation during adolescence and adulthood. Notable exceptions are the works of Lehmann and Wadsworth (2011) and Danzer and Danzer (2016), who document a negative effect of the Chernobyl-reduced radiation on earnings, health and well-being in Ukraine, the country where Chernobyl is located. Our paper provides further evidence of a causal effect of low-dose radiation on cognitive performance. Moreover, our results point to even wider-reaching adverse effects of nuclear disasters. Germany is over 1200km from Chernobyl, and our study shows that large parts of the population have been adversely affected.

This result feeds into two domains of the public debate. One is about the costs and

[1]For a recent review of the literature on early-childhood exposure, see Almond et al. (2018). Besides the studies on radiation cited in the text, prominent examples include exposure to air pollution (Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie et al., 2009a,b; Currie and Walker, 2011; Coneus and Spiess, 2012; Sanders, 2012; Tanaka, 2015; Bharadwaj et al., 2016; Isen et al., 2017; Rosales-Rueda and Triyana, 2018; Simeonova et al., 2021), lead (Feigenbaum and Muller, 2016; Aizer et al., 2018; Billings and Schnepel, 2018; Aizer and Currie, 2021) and temperature shocks (Deschenes et al., 2009). Examples for studies exploiting short-run effects of air pollution are Ebenstein et al. (2016); Persico and Venator (2021); Heissel et al. (2021) (test scores), Graff Zivin and Neidell (2012), Chang et al. (2016) and Lichter et al. (2017) (productivity), Künn et al. (2019) (cognitive performance), and Schlenker and Walker (2011); Mullins and Bharadwaj (2015) (health).

benefits of nuclear power in many countries. While nuclear power offers the advantage of supplying vast amounts of energy at zero carbon emissions, it comes with the cost of potential disasters. In the last 35 years we have seen two major disasters, and given the proliferation of nuclear power around the world, more might follow. Our results, along with those in other studies, point to significant external costs of nuclear power. Another public debate, more broadly, deals with exposure to man-made radiation. For example, today the average American receives twice the annual radiation dose compared to 1980, which is mainly due to medical procedures such as x-rays, mammograms or CT scans.[2] Our results can inform the debate about the long-term consequences of this increase in radiation exposure. The radiation dose from these procedures is similar to the additional radiation dose Germans in highly affected areas received after Chernobyl. Our results suggest that low-dose radiation can have negative long-term effects on cognitive skills.

2 Historical Background and Review of the Medical Literature

2.1 The Chernobyl Disaster and its Impact in Germany

The Chernobyl nuclear disaster in 1986 is one of the two largest nuclear accidents in history. It occurred after a failed simulation of a power cut at a nuclear power plant in Chernobyl/Ukraine on April 26, 1986, which triggered an uncontrolled chain reaction and led to the explosion of the reactor. In the two weeks following the accident, several trillion Becquerel of radioactive matter were emitted from the reactor, stirred up into the atmosphere, and – through strong east winds – carried all over Europe.[3] The most affected countries were Belarus, Ukraine as well as the European part of Russia, although other regions, such as Scandinavia, the Balkans, Austria and Germany also received considerable amounts of fallout. The only other accident with comparable levels of fallout was the Fukushima disaster in Japan in 2011 (Yasunari et al., 2011).

Post-Chernobyl radiation in Germany The radioactive plume reached Germany three days after the disaster, on April 30, 1986. It first entered the country in the south-east and made its way north-west before disappearing over the North Sea on May 8. The fallout comprises four main isotopes, namely caesium-137 (Cs137), caesium-134 (Cs134),

[2]Source: National Council on Radiation Protection and Measurements (2009).

[3]Becquerel (Bq) is a unit of radioactivity. One Bq defines the activity of radioactive material in which one nucleus decays per second. In the following, we use kilobecquerel (kBq). One kBq equals 1000Bq.

strontium-90 (Sr90) and iodine-131 (I131), which have half-lives of up to 30 years.[4] Among the four isotopes, soil-bounded Cs137 is today considered the only relevant source of radiation in Germany that can be ascribed to the Chernobyl disaster (Hachenberger et al., 2017). From 1986 to 1989, the governments of West and East Germany rolled out a comprehensive program to measure radiation across the country. At over 3,000 temporary measuring points, gamma spectrometers measured the radiation of Cs137. Based on the decay of the isotopes, all measurements were backdated to May 1986.

Figure 1a displays the ground deposition of Cs137 in May 1986. The deposition of the fallout varies considerably across regions due to differences in rainfall, wind, topography and other factors. Because Cs137 rarely occurred in Germany before 1986, the displayed variation is almost entirely due to the Chernobyl fallout. The regions that received the highest level of fallout were Bavaria and Baden-Wuerttemberg in the south as well as parts of the former German Democratic Republic. Across Germany, the level of ground deposition ranges from 0.224 kBq/m^2 to 107 kBq/m^2. For comparison, soil is officially considered contaminated if the radioactivity exceeds 37 kBq/m^2 (UNSCEAR, 2000). The majority of the population lived in areas with radiation levels below 20 kBq/m^2, although a non-negligible number of people lived in areas with levels much higher than that.[5]

Radiation exposure of the German population Humans can be exposed to radiation in three ways, namely through inhaling radioactive particles, ingesting contaminated foods, as well as external exposure, whereby radiation affects the body if a person is present in a place with a given level of radioactivity in the environment. Exposure to radiation through air and ground can be directly assigned to – and therefore strongly correlated with – a person's place of residence (Clark and Smith, 1988). By contrast, exposure through food may not necessarily result from contamination in the same locality, given that the food might have been produced elsewhere. In the northern hemisphere, the average yearly exposure to natural radiation is 2.4 mSv, of which 52% is through inhalation, 12% through ingestion, and 36% through terrestrial and cosmic radiation (UNSCEAR, 2008). The degree of exposure differs between people and depends on their daily activities and diet.

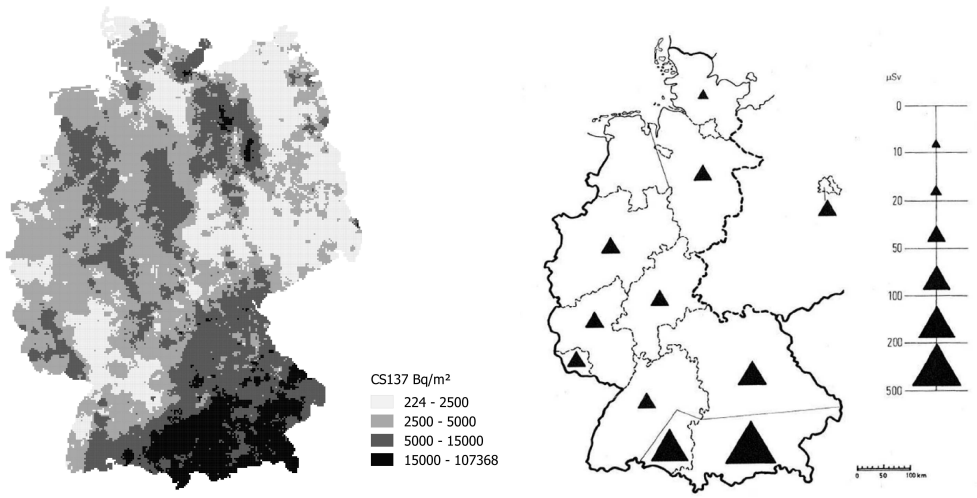
The exposure to the Chernobyl radiation peaked in the first days after the radioactive rainfall and has been gradually declining since. While during the first days the largest source of exposure was inhalation of radioactive particles, later on people were mainly exposed through ingestion and external exposure. The German Agency for Radiation

[4]The half-lives of the four isotopes are eight days (I131), two years (Cs134), 28.8 years (Sr90), and 30.2 years (Cs137). We will use the abbreviations in parentheses further in the paper. These do not correspond to the abbreviations used in chemistry, which are ^{137}Cs, ^{134}Cs, ^{90}Sr and ^{131}I.

[5]See Figure 5b in Appendix A.4 for the distribution of ground deposition in the German population.

Protection (BfS) estimates that the dose in the first year – when radioactive particles were in the air and, in general, the radiation was highest – accounted for 21% of the cumulative dose over 25 years. In 1987, the dose accounted for 11%, and – due to the decay of the radioactive matter – it has been declining at an annual rate of 4% since. The cumulative effective radiation dose induced by Chernobyl – the total dose that entered the tissue of an average person – was 0.6mSv, which is comparable to the dose from 30 chest x-rays. However, the doses significantly varied across regions. In Munich, one of the most affected cities, the cumulative effective dose was 2.1mSv.

Due to its long half-life, the nuclear fallout represented a quasi-permanent shock to radiation levels. A person who has been living in a highly-affected area for the last 25 years has been exposed to higher airborne radiation initially as well as higher ground radiation over the entire time compared someone living the entire time in a less affected area. In 2010, the first year in which we measure people's cognitive performance, more than half of the fallout was still in the ground, although over time it has been washed out into deeper layers of soil, thereby reducing the external exposure of the population (Bunzl et al., 1995). However, exposure through ingestion is possible until today, as certain foods – in particular mushrooms and game – still exceed radiation limits in parts of South Germany.



(a) Ground deposition of CS137 (b) Information released in 1986

Figure 1: Ground contamination in 1986

Notes: These graphs display (a) the ground deposition of Cs137 in Bq/m^2 and (b) the information about regional exposure in mSv that was released to the public in 1986. Source: Federal Office for Radiation Protection (Bundesamt für Strahlenschutz), German-Swiss Association for Radiation Protection (Fachverband für Strahlenschutz e.V.)

Information about the nuclear disaster and reactions of the German public

The German public learned about the nuclear accident several days after it occurred, and

– in most parts of the country – after the radioactive rain had fallen. Indications of a nuclear accident were first noticed in Sweden, where scientists measured abnormally high levels of radioactivity at the Forsmark nuclear power plant. The Soviet Union initially released no information about the accident, and its government only acknowledged it after the information from Sweden had spread. The German population was officially informed for the first time during the newscast "Tagesschau" on April 29, which reported about high levels of radioactive matter being emitted from an exploded nuclear power plant in Ukraine. In the same newscast, the Federal Minister of the Interior, Friedrich Zimmermann, stated that, due to the distance to Ukraine, there was no danger for the German population. However, two days later, after high radiation levels were measured in several parts of the country, the government of the Federal Republic of Germany (FRG) introduced radiation limits on foods and warned the population of the consumption of dairy produce, vegetables, mushrooms and game, which were potentially contaminated. In the following days, contaminated food was discarded and public swimming pools and playgrounds were temporarily closed. Despite these measures, the German government maintained its official communication that the increased radiation did not present a health hazard to the population. The information policy differed considerably between the FRG and the German Democratic Republic (GDR). In the GDR, no comparable measures were put in place. Quite the opposite, after the accident and the collapse of demand in the FRG, agricultural products intended for export to the FRG were supplied to the market in the GDR.

While the German population was generally informed about the radioactive fallout, they had little knowledge about the levels of fallout in particular areas. Figure 1b shows a map released by the German-Swiss Association for Radiation Protection in 1986, which displays the average exposure in mSv in twelve large regions. A detailed map, such as the one shown in Figure 1a only became available five years later, in 1991. This means that the public only learned about the amount of radiation in their municipality of residence five years after the disaster.

Although there is plenty of anecdotal evidence that people changed some behaviors after the disaster – diet, physical activity, time spent outside –, it appears that these changes were short-lived. For example, Renn (1990) shows that Germans' attitudes in favor of nuclear energy reverted to their pre-1986 levels one year after the accident.

2.2 Effects of Radiation on the Human Body

The effect of radiation on the human body is by no means limited to high-dose radiation, such as the one experienced by survivors of nuclear bombs or clean-up workers at the site

of the Chernobyl reactor. The medical literature has shown that exposure to subclinical radiation – at doses most people are exposed to, for example due to background radiation, medical procedures, or the fallout from Chernobyl in large parts of Europe – can negatively affect cognition, physical health and well-being. Moreover, while the effects of subclinical radiation may be strongest during pregnancy and early childhood, radiation exposure can have adverse effects throughout a person's life.

Plausible channels. Radiation exposure can affect cognitive test scores through four types of channels:

1. A **direct effect on cognition**, as radiation can impair the functioning of brain cells.

2. An **indirect effect through physical health**; radiation can impair the functioning of organs and lead to greater fatigue, which in turn may negatively affect test scores.

3. An **indirect effect through mental health**; a review by Bromet et al. (2011) suggests that people's worry about the long-term consequences of radiation for physical health may lower their well-being and lead to poor mental health.

4. Indirect effects through **behavioral responses**, such as internal migration or changes in life style. To the extent that these effects reflect avoidance behavior, they will dampen the negative biological effects.

In the following, we summarize the evidence from two types of study: one based on observational studies with humans, the other based on experimental studies with mice and rats. While both arguably have their weaknesses – one is non-experimental, the other has limited external validity – together they show that an effect of radiation on cognitive test scores is biologically plausible.

Observational studies. The effect of radiation on cognitive performance is an active field of research in radiobiology and medicine. Radiation affects the human body through ionization, a process that damages the DNA and can lead to the dysfunction or death of cells (Brenner et al., 2003). Until the 1970s the human brain was considered radio-resistant, that is, brain cells were assumed to be unaffected by radiation. This view changed when lasting cognitive impairments were found in cancer patients who underwent radiotherapy. Studies find cognitive impairments among 50-90% of adult brain cancer patients who survive more than six months after radiotherapy. The cognitive impairment can manifest itself in decreased verbal and spatial memory, lower problem-solving ability and decreased attention, and is often accompanied by fatigue and changes in mood

(Greene-Schloesser and Robbins, 2012). In extreme cases, it may even lead to dementia (Begum et al., 2012).

Laboratory evidence on rats and mice The experimental evidence with rodents confirms the evidence found among human cancer patients. Rats who were treated with brain irradiation experience a reduction in cognitive ability, although the biological processes differ between young and old rats. The response among young rats is mainly driven by a reduction in neurogenesis – the production of new neurons – and the loss of mature neurons. Among adult rats, neurogenesis plays a less important role (Monje et al., 2002; Schindler et al., 2008; Shi et al., 2008). Rather, the effect of radiation on cognitive impairment works through the dynamic interaction of several biological processes, such as vascular damage (Reinhold et al., 1990; Brown et al., 2005, 2007), the functioning of astrocytes and neurons, as well as inflammation and oxidative stress (Robbins and Zhao, 2004).[6]

While these studies confirm that radiation can plausibly affect cognitive functioning across the life cycle, they are mostly based on once-off radiation treatments. In contrast, after Chernobyl, the German population was constantly exposed to higher ground radiation for many years. A recent experiment on mice by Kempf et al. (2016) is informative about the effect of *regular* exposure to low-dose radiation. Among mice who were exposed for 300 days, the researchers detected a decrease in cognitive functioning and a higher incidence of Alzheimer's disease.

Impact on overall health Radiation can also indirectly affect cognitive test scores through its general impact on health. Holding the functioning of the brain constant, we would expect worse physical health and lower well-being to reduce performance in a cognitive test. While the medical literature most frequently studies extreme outcomes such as cancer and mortality, there is growing evidence that subclinical radiation can impede the functioning of organs (Vaiserman et al., 2018), which may have a variety of knock-on effects. For example, within-estimates among radiotherapy patients show that radiation exposure significantly increases inflammation risk and fatigue (Bower et al., 2009). There is also correlational evidence that radiation exposure is associated with a lower functional capacity of the lungs (Hill, 2005) and a higher risk of cardiovascular disease (Kreuzer et al., 2006; Zielinski et al., 2009). While these studies may not be able to identify causal effects, they underline the plausibility of low-dose radiation having adverse health effects.

[6]See Greene-Schloesser and Robbins (2012) for a review of the oncological literature. Astrocytes are glial cells in the central nervous system.

3 Data and Descriptive Statistics

We link rich individual-level survey data with geo-coded information on radiation in a person's municipality of residence in May 1986. In this section, we describe the construction of the dataset as well as the measurement of cognitive performance, and present descriptive statistics. We limit the description of the dataset to the most important aspects. In addition, in Appendix A, we provide more detailed information and perform a large number of balancing tests to ensure that the estimation results are not driven by sample selection.

3.1 The NEPS Data

Our main data source is the NEPS, a rich representative dataset on educational trajectories in Germany. NEPS offers two features that are key to our analysis. First, the survey includes standardized competence tests that allow us to measure cognitive performance along various dimensions for people aged between 24 and 58 years in 2010. This represents a significant advantage over most datasets that include information on cognitive performance – notably the Scandinavian population register data – which typically only measure skills at school-leaving age (i.e. 18 or 19). Second, the NEPS includes detailed information on residential histories. For each respondent, it provides monthly spell data on their municipality of residence since their birth, allowing us to link personal characteristics and cognitive test scores measured after 2009 with data on radiation levels in the person's municipality of residence in May 1986.

The NEPS is supervised and hosted by the Leibniz Institute for Educational Trajectories (LIfBi, Blossfeld et al. (2011)). It comprises six starting cohorts, ranging from newborns to adults, which have been followed in multiple waves since 2010. In this study, we use the adult cohort of the NEPS (Starting Cohort 6 – SC6). More specifically, we use the so-called ALWA subsample of the adult cohort, which includes respondents born between 1956 and 1986. To set up the NEPS SC6, LIfBi took over a representative survey named Working and Learning in a Changing World (ALWA), which was conducted by the Institute for Employment Research (IAB) in 2007 with originally 10,404 respondents. The original aim of ALWA was to study geographic and occupational mobility, which is why IAB devoted considerable resources to eliciting residential and occupational histories. For further information on how this information was gathered, see Appendix A.1.

The NEPS SC6 includes all respondents of ALWA who were willing to enter the panel and be surveyed every year (N=8,997). Among those who agreed to be included, 6,572

actually participated.[7] A comparison of the ALWA subsample with the German Microcensus shows that the sample is representative of the German population, although people with higher education and older people are slightly over-represented, whereas migrants are under-represented.

3.2 Estimation Sample

Our sample includes all survey participants who were born *before* Chernobyl. We exclude participants born after Chernobyl because the survey only sampled birth cohorts up to December 1986, leaving us with few participants who were born after Chernobyl. Moreover, because we are interested in the effect of post-natal exposure, excluding them ensures that our estimates are not confounded by exposure in utero, which operates through a different biological channel. Overall, we can link the municipality of residence in May 1986 for 5,844 participants. For the remaining 728 participants, we could not link the data due to missing municipality keys (402 obs.) or because they lived abroad in May 1986 (326 obs.). Observations with missing municipality keys include 140 participants born after April 1986.

To reduce classification error, we drop respondents who moved in May 1986 (34 obs.), for whom we cannot determine whether they moved before or after the radioactive plume reached Germany. We also drop all respondents who did not participate in the competence tests (1,265 obs.), as well as all participants for whom information on personal characteristics is missing (105 obs.). Our final estimation sample comprises 4,440 observations. In Appendix A.1, we provide a detailed description of the sample design and the actions taken by the interviewers to minimize recall error when eliciting the residential history. Moreover, in order to address concerns about the representativeness of the estimation sample, we perform a series of balancing tests in Appendix B, which suggest that the missing information is unsystematic.

3.3 Cognitive Tests

One of the core objectives of the NEPS SC6 was to collect data on the competencies of adults. The survey includes eight standardized cognitive tests that were modeled after well-established tests from psychology and related fields (Weinert et al., 2011). For our analysis, we use tests on *mathematical competence*, *reading competence*, *scientific literacy*, *listening comprehension*, *ICT literacy*, *reading speed*, *perceptual speed*, and *reasoning*. In the empirical analysis, we use each test score as a separate outcome. In order to make the

[7] Of the 2,425 respondents who did not participate despite agreeing, 68% were unwilling, while 32% could not be contacted.

estimates comparable across outcomes, we standardize the test scores to a mean of zero and a standard deviation of one. Moreover, given that the test scores measure different aspects of the latent variable cognitive skills, we construct a standardized cognitive skills index, which we construct by summing over all eight standardized test scores and standardizing this sum to a mean of zero and a standard deviation of one. Using the same standardization, we construct sub-indices for skills governed by crystallized intelligence (math, reading, science, listening, ICT) and fluid intelligence (reading speed, perceptual speed, reasoning).

3.4 Municipality- and County-level Data

Data on ground deposition Our regressor of interest is the ground deposition of Cs137 in kBq/m^2 in May 1986, which we use as proxy for Chernobyl-induced radiation in Germany. The regional concentration of Cs137 is strongly correlated with other Chernobyl-induced sources of radiation such as I131 or Sr90 (Hou et al., 2003), although Cs137 is easier to measure and – due to its long half-life – mainly responsible for the long-run exposure of the population (International Atomic Energy Agency, 2006).

The Federal Office for Radiation Protection (Bundesamt für Strahlenschutz, BfS) provided us with geo-coded data for the soil surface contamination in Germany at 3,474 measurement points in May 1986. The data were compiled by the BfS following a comprehensive measurement program rolled out between 1986 and 1989. Measurements taken after May 1986 were backdated based on the decay of Cs137. For each municipality centroid, we calculate the radiation level as the inverse-distance weighted average from the four closest measuring points.[8] After 1989, no comparable radiation data are available. Therefore, we know the *initial* level of radiation in area, but we have no information how radiation levels developed between 1989 and 2010. It is possible to calculate the approximate radiation level based on the decay of Cs137, although to determine the exact level we would need to know the extent to which the radioactive matter was washed into deeper layers of soil.

Linkage between individual and regional data We link the radiation data for 1986 with the individual survey data based on the respondents' municipality of residence in May 1986, using the radiation level in the centroid of the municipality. This linkage provides us with a measure of potential exposure to the post-Chernobyl radiation for

[8] This is the same way the German Agency for Radiation Protection calculates radiation levels. Given the large number of measurement points, most municipalities had four measuring points in close proximity. In Appendix B.2, we also run a robustness check wherin we calculate radiation levels based on the closest measuring point.

each person in the sample.[9] Because we link the data without knowing the precise place of residence within a municipality, the linkage inevitably introduces measurement error. We address this problem in several robustness checks in Appendix B.2, which show that the results are robust to different linkage procedures.

Additional data We supplement our dataset with municipality- and county-level data on geographic conditions and population characteristics. We obtained data on precipitation, altitude and population size at the municipality level and data on minimum altitude and the composition of the population at the county level.

3.5 Descriptive Statistics

Table 1 displays the descriptive statistics of the main variables used in the regression. In 1986, the average person in the sample was 19 years old, with ages ranging from zero to 30 years. 36% of the sample – predominantly the older cohorts – were employed at the time, while another 43% were enrolled in education, and 1% were unemployed. The share of people who lived in the GDR represents 18% of the sample.

The German secondary school system has three tracks, namely lower secondary school (*Hauptschule*, graduation after 9 years of schooling), intermediate secondary school (*Realschule*, 10 years), and upper secondary school (*Gymnasium*, 12 or 13 years). People with an upper secondary school degree can pursue a tertiary education, whereas people with lower degrees typically enter vocational training after graduating. 45% of the sample were no longer in education in April 1986: 4% had a lower secondary or secondary, while 28% and 13%, respectively, had an upper secondary or tertiary degree. On the other hand, 43% were still in education, most of whom had not yet finished a degree (31% of the sample). 10% of the sample were enrolled in 1986 but had already passed lower secondary or secondary education, while 1% had passed upper secondary education.

The dataset also includes information on the highest school degree of the respondents' parents. The statistics reflect the seminal changes in the German education system, whereby the generations born until the 1950s and earlier had much lower educational attainment than their children. Over half of all respondents have parents with no more than nine years of schooling.

The fourth set of statistics describe the cognitive test scores. Two features are note-

[9] The German Federal Agency for Cartography and Geodesy (BKG) provided us with a list of all municipalities according to the definition as of 2013, their official municipality keys, as well as the geo-codes of the municipality centroids. Due to confidentiality issues, the NEPS does not release the municipality keys to its users, but the LIfBI offers to merge data at the municipality level. We are very grateful for this service.

worthy here. First, each test has a different metric, resulting in differences in means and standard deviations. Without a standardization, the estimates will be difficult to interpret and compare. Second, the number of observations differs between tests, which is due to design features of the NEPS (see Section 3.3 and Appendix A).

Panel B displays the municipality-level characteristics. With the exception of dementia incidence, the statistics were computed across individual observations in the estimation sample. The mean ground deposition of Cs137 in May 1986 amounts to 5.18 kBq/m^2. The standard deviation – which is larger than the mean – points to a significant variation in ground deposition across Germany.[10] Based on a person's residential history between 1986 and 2010, and using the decay formula for Cs137, we also compute the average level a person is exposed to over the 25-year period. Because of the decay, the average level of Cs137 is smaller than the initial level, amounting to 3.89kBq/m^2.

The level of precipitation represents the average rainfall in May in the five years preceding the Chernobyl disaster, i.e. 1981-1985. The final two statistics describe two altitude measures that are important determinants of radiation. They jointly determine orographic rainfall, which in turn affects the level of radiation after the disaster.

[10]See Appendix A.4 for an illustration of the distribution of the ground deposition across municipalities.

Table 1: Descriptive statistics of the main variables

	Mean	SD	min	max	N
A. Individual-level data					
Personal characteristics					
Age in 1986	19.05	8.20	0.00	30.43	4440
Female	0.51	0.50	0.00	1.00	4440
GDR	0.18	0.39	0.00	1.00	4440
Unemployed in April 1986	0.01	0.12	0.00	1.00	4440
Employed in April 1986	0.36	0.48	0.00	1.00	4440
Educational attainment in April 1986					
Not of school age yet (less than 7 years old)	0.12	0.33	0.00	1.00	4440
No degree, lower secondary, secondary	0.04	0.19	0.00	1.00	4440
Upper secondary	0.28	0.45	0.00	1.00	4440
Tertiary	0.13	0.33	0.00	1.00	4440
In school or college education,	0.43	0.49	0.00	1.00	4440
no degree	0.33	0.47	0.00	1.00	4440
already attained lower secondary, secondary	0.10	0.31	0.00	1.00	4440
already attained upper secondary	0.01	0.09	0.00	1.00	4440
Highest parental education					
Lower secondary	0.52	0.50	0.00	1.00	4440
Secondary	0.27	0.44	0.00	1.00	4440
Upper secondary	0.21	0.41	0.00	1.00	4440
Test Scores					
Math	11.32	4.75	0.00	21.00	2652
Reading	27.06	7.45	0.00	39.00	2666
Reading Speed	38.19	8.34	0.00	51.00	3611
Scientific literacy	19.00	5.29	0.00	30.00	3286
ICT	41.20	13.62	0.00	66.00	3312
Reasoning	8.94	2.38	0.00	12.00	3169
Listening comprehension	75.82	7.97	0.00	89.00	3172
Perceptual Speed	34.68	8.07	0.00	82.00	3170
B. Municipality-level data					
Caesium137 kBq/m^2 (01. May 1986)	5.18	5.87	0.50	62.10	4440
Precipitation mm/m^2 (yearly average, 1981-1985)	3.09	0.84	1.30	8.00	4440
Altitude in meter	201.59	176.69	0.00	850.00	4440
Minimum altitude in meter in county	138.73	139.78	-1.00	660.00	4440

Notes: This table displays the descriptive statistics for the variables used in the analysis. The number of observations varies between tests due to the survey design. See Appendix A for a comprehensive description of the testing procedure. The data underlying the statistics in Panel B are measured at the municipality level and in C at the county-level, although the statistics themselves are computed at the individual level. The statistics for dementia cases are measured at the municipality-level.

4 Empirical Strategy

Our goal is to estimate the causal effect of Chernobyl-induced radiation exposure over the period 1986-2010 on cognitive test scores measured in and after 2010. In this section, we discuss the identification strategy in two steps. We first discuss the variation in ground deposition and under what conditions we can leverage this variation to identify a causal effect. In a second step, to address the potential identification challenges posed by unobserved heterogeneity, we propose an instrumental variable strategy that exploits unexpected rainfall levels during a critical time window after the disaster as well as the trajectory of the plume. We also discuss challenges to statistical inference.

4.1 Empirical Model

To quantify the effect of radiation exposure on cognitive performance, we estimate versions of the linear regression model

$$y_{ims} = \alpha + \beta \; Cs137^{86}_{ims} + \boldsymbol{X'_{im}}\boldsymbol{\gamma} + \delta_s + \varepsilon_{ims}. \tag{1}$$

The outcome y_{ims} is the cognitive test score of person i who resided in municipality m in state s in May 1986, which we regress on the level of ground deposition of caesium-137 in the person's municipality of residence in May 1986. Because $Cs137^{86}_{ims}$ reflects the *initial* level of exposure, β is to be interpreted as an intention-to-treat (ITT) effect. The ITT effect comprises all channels through which radiation exposure affects cognitive test scores, such as the direct effect on cognitition as well as indirect effects through health or changes in behavior. Although the ITT effect is estimated from the initial exposure in 1986, the estimate reflects the exposure over the entire sample period 1986-2010, as areas with higher initial radiation were more exposed throughout.

In our most comprehensive specification, we control for pre-determined individual, county and municipality characteristics, which are summarized by $\boldsymbol{X_{im}}$. At the individual level, $\boldsymbol{X_{im}}$ includes controls for gender, a quadratic in age, as well as indicators for whether a person is a German native speaker, the person was born in Germany, parental education levels, own education level in 1986 and own employment status in 1986. In terms of municipality and county characteristics, we include average daily rainfall between 1981 and 1985 and altitude, which are both important determinants of Cs137 and potentially correlated with local determinants of cognitive performance.[11] To capture features of

[11] The controls for altitude include two variables, namely the altitude at the municipality centroid as well as the minimum altitude in a given county. The combination of these two variables has been shown to be a determinant of orographic rainfall (Houze, 2012), which in turn has been shown to increase the level of fallout (Yasunari et al., 2011). Appendix A.3 provides further details on the control variables.

the survey design, we further control for the year in which a test was taken as well as membership in one of four test groups, each of which took the cognitive tests in a different sequence.

In our preferred specifications, we also condition on state fixed effects, δ_s, which means that we compare people who lived in the same state but in different municipalities in 1986.[12] The fixed effects are important as they absorb differences across states that could otherwise drive the results. The quality of education in Germany differs across states, which may explain some of the variation in test scores and be correlated with the level of exposure – Figure 1 shows that high-exposure areas are clustered in the southern states, which tend to have higher average scores on standardized tests (Baumert et al., 2002).

The error term ε_{ims} summarizes all determinants of cognitive test scores that are not captured by the regressors. We discuss challenges to statistical inference such as clustering and multiple hypothesis testing in Section 4.4 below.

4.2 Identification Assumption and Balancing Tests

The coefficient β can only be interpreted as causal if the local fallout level is as good as randomly assigned and, thus, the following identification assumption holds:

$$E[\varepsilon_{ims}|Cs137_{ims}, \boldsymbol{X_{im}}, \delta_s] = 0. \tag{2}$$

A common challenge in studies on exposure to pollution does not apply here, namely anticipation effects. People could neither foresee the Chernobyl disaster nor the local level of fallout. It is implausible that people moved to a different place before the disaster to avoid exposure to fallout stemming from an exploded reactor 1,200km away. Anticipation effects are to be distinguished from avoidance behavior in response to the disaster, such as internal migration or changes in lifestyle. Other than anticipation effects, avoidance behavior would not violate the identification assumption (2), although it would change the interpretation of the reduced-form coefficient β. In presence of avoidance behavior, β is to be interpreted as the total effect of radiation on cognitive skills, which includes all biological and behavioral responses.

However, the fact that the disaster was unanticipated may not mean that the geographic variation of Cs137 was completely random. A potential challenge for identification is that some areas may be more prone to higher radiation levels than others, for example due to differences in precipitation or topography. The proneness, in turn, may

[12] In line with the state borders of 1986, we treat the GDR as one state, which results in a total of twelve states. East Berlin is counted as part of the GDR, while West Berlin is considered a state of its own. The results are robust to fixed effects with all sixteen post-1990 states. These results are available on request.

be correlated with determinants of cognitive test scores through residential sorting. For example, if rural areas are more prone to higher radiation levels and people with lower unobserved skills disproportionately live in rural areas, we would obtain a negative correlation between radiation and cognitive test scores. However, this correlation would be the result of residential sorting, rather than representing the causal effect of radiation on test scores. If the assignment of ground deposition was as good as random, it would break the spurious correlation due to residential sorting.

Balancing tests To corroborate the identification assumption in Equation (2), we perform balancing tests whereby we eamine to what extent local fallout is correlated with individual pre-determined characteristics. Each coefficient in Table 2 is the result of a regression of a pre-determined variable on the left on the ground deposition of Cs137, controlling for the variables listed at the bottom. In this test, statistically significant coefficients would be an indication that the variation in Cs137 is not as good as random.

The raw correlations in Column (1) show that the local fallout level is uncorrelated with most – but not all – observable characteristics. Respondents whose parents had a lower education were more exposed to radiation, which suggests that residential sorting may indeed be correlated with fallout levels. However, this correlation disappears when we gradually introduce controls and fixed effects. In Column (4), when we condition on state fixed effects and control for altitude and rainfall, all coefficients are close to zero and only one out of 14 coefficients is statistically significant at the 10%-level, which is consistent with sampling variation around a true value of zero. This result indicates that there was no selection into high exposure based on observable characteristics, which supports the identification assumption in Equation (2).

What about internal migration? A conceptual challenge with our empirical strategy is internal migration. While it is implausible that people move in anticipation of the disaster, one concern might be that people move *in response* to the disaster in order to avoid a high exposure. This type of migration would not be a confounder – after all, the migration is caused by radiation – but it would change the interpretation of the coefficient β. If people disproportionately leave highly contaminated areas we would obtain a lower estimate of β compared to a world without internal migration. As shown in Table 3, after Chernobyl a significant share of the sample moved from their initial municipality of residence. Until January 1, 1988, 12.2% moved, whereas until 2010, close to 60% moved. In Columns (1) and (2), we find no evidence that internal migration was systematically related to fallout levels. In regressions of migration indicators on the ground deposition of Cs137, we find estimates that are close to zero with small standard errors.

Table 2: Balancing tests

Regressor:	Cs137 (1)	Cs137 (2)	Cs137 (3)	Cs137 (4)	IV (5)
A. Individual characteristics					
Age in 1986	0.008	0.019	0.021	0.007	0.209
	(0.023)	(0.028)	(0.028)	(0.032)	(0.258)
Female	-0.001	-0.002	-0.002	-0.002	0.005
	(0.001)	(0.001)	(0.001)	(0.002)	(0.014)
Employed in April 1986	0.001	0.002	0.002	0.003*	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.015)
Unemployed in April 1986	-0.000	0.000	0.000	-0.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
If employed : Qualified or highly qualified	0.002	-0.000	-0.001	0.001	-0.024
	(0.002)	(0.002)	(0.002)	(0.002)	(0.022)
Children before 1986	-0.002**	-0.002	-0.002	-0.000	0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
Smoke before 1986	0.001	0.001	0.001	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)
Educational attainment in April 1986					
Lower secondary and secondary	0.001	0.002	0.002	0.001	0.009
	(0.001)	(0.002)	(0.002)	(0.002)	(0.014)
Upper secondary	0.000	0.000	0.000	0.002	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
Tertiary	-0.002	0.000	0.000	-0.005	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.017)
In school or college education	0.000	0.000	0.000	0.000	0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)
Highest parental education					
Lower secondary education	0.000	0.001	0.001	0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)
Secondary education	0.005***	0.004**	0.004**	0.001	0.016
	(0.001)	(0.002)	(0.002)	(0.002)	(0.018)
Upper seconary	-0.003***	-0.000	-0.000	0.000	-0.013
	(0.001)	(0.001)	(0.001)	(0.001)	(0.013)
Controls:					
Altitude	No	Yes	Yes	Yes	Yes
Average rainfall	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes

Notes: This table displays regression-based balancing tests. Each coefficient in Columns (1)-(4) is the result of a separate regression of the pre-treatment characteristics on the left on the level of Cs137 in a person's municipality of residence in May 1986, controlling for the variables listed at the bottom. In Column (5), the regressor is the instrument $\ln(rain_m^{86} \times matter_m)$ introduced in Section 4.3. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

4.3 Instrumental Variable Strategy

Although the balancing tests in Table 2 do not point to selection on observables, it might still be possible that our results are driven by unobserved heterogeneity. The concern is

Table 3: No evidence of a migration response

	Share of movers since 1 May 1986	(1)	(2)
Migration until 1988	12.2%	0.000	0.000
		(0.001)	(0.001)
Migration until 1990	23.5%	0.000	0.000
		(0.001)	(0.002)
Migration until 1995	39.4%	-0.001	-0.003
		(0.001)	(0.002)
Migration until 2010	59.5%	0.001	0.001
		(0.001)	(0.002)
State FE		no	yes
Controls		no	yes

Notes: This table reports the results of OLS regressions of migration indicators on the level of Cs137 in 1986. Each entry in Columns (1) and (2) is the result of a separate regression. The binary indicators equal unity if a person moved out of their municipality of residence between May 1986 and January 1 of the year indicated on the left. In Column (2) we control for individual, geographic and survey characteristics as well as state fixed effects. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

that people with higher unobserved ability may have lived in places with systematically higher or lower radiation levels. We address this concern through an instrumental variable strategy that isolates variation in fallout that is plausibly uncorrelated with unobserved determinants of test scores. Local fallout is driven by the interplay of three main determinants, namely i) the amount of radioactive matter in the plume in a given place, ii) weather conditions, and iii) topography. The amount of radioactive matter in the plume declined as the plume was moving from the south-east to the north-west of the country and more and more radioactive matter had been rained down. This means that the contamination was higher in the south because the same amount of rainfall carried more radioactive matter than in the north. Figure 2 illustrates the trajectory of the plume based on air concentration measurements at four stations. In the south-eastern-most station (Brotjacklriegl), the concentration of radioactive particles was very high on April 29 and sharply declined thereafter. When the plume reached the stations in the center of Germany (Offenbach and Neuherberg) on May 1 and 2, the initial concentration was lower than in the south-east, whereas the curve is almost flat in Norderney, the north-western-most station. A second important determinant of local fallout was the amount of rainfall while the plume was above an area. In areas with little rainfall, the amount of fallout was low. A third determinant is topography. The same amount of radioactive matter that was rained down may result in different levels of measured ground deposition depending on the slope and the type of surface. For example, unsealed surfaces such as open fields or parks absorb more radioactive matter than sealed surfaces.

Among the determinants of local fallout, our instrument isolates two that are plausibly exogenous to a person's cognitive skills, namely the amount of rainfall in a critical time window of ten days and the amount of available radioactive matter in the plume. On the other hand, we exclude determinants such as altitude or soil conditions, which are most likely correlated with residential sorting and, therefore, would invalidate the instrument. We construct the the instrument

$$z_m = rain_m^{86} \times matter_m \tag{3}$$

by interaction the amount of rainfall in municipality m between April 29 and May 8, 1986, with the amount of radioactive matter in the plume. We calculate $matter_m$ based on air concentration measurements of radioactive matter.[13]

[13] We calculate the air concentration of radioactive matter based on measurements of sixteen measuring stations in Germany immediately after the disaster (April 29-May 8, 1986). Data on these measurements are provided by European Commission (1998). For each municipality, we compute the variable $matter_m$ as the inverse-distance-weighted average of the three closest measuring points.

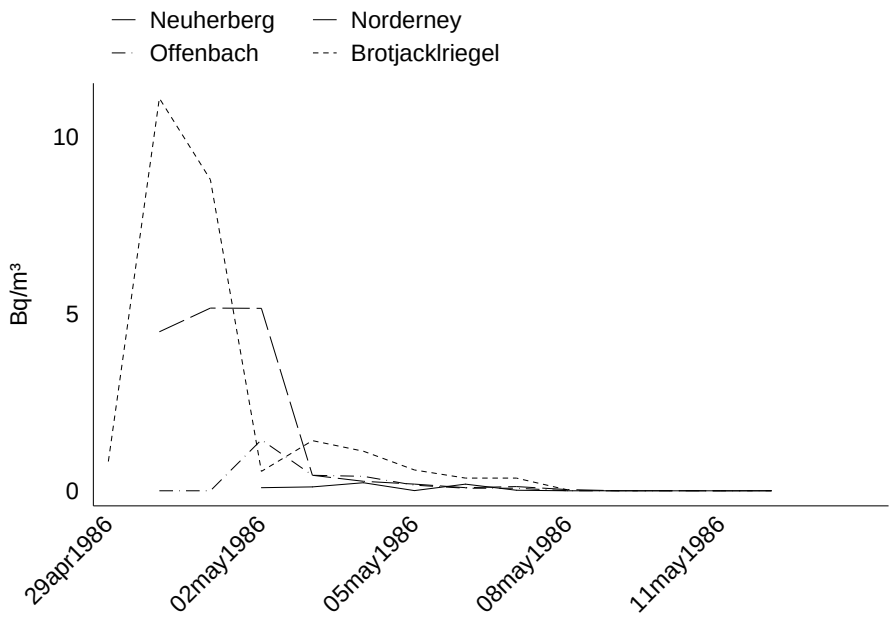


Figure 2: Air concentration of radioactive particles in 1986

Notes: This graph displays the air concentration of Cs137 measured after the arrival of the radioactive plume in four German measuring stations. These are located in different parts of the country: Brotjacklriegel (south-eastern border), Neuherberg (south-east), Offenbach (center) and Norderney (north-west). Source: Federal Office for Radiation Protection (Bundesamt für Strahlenschutz).

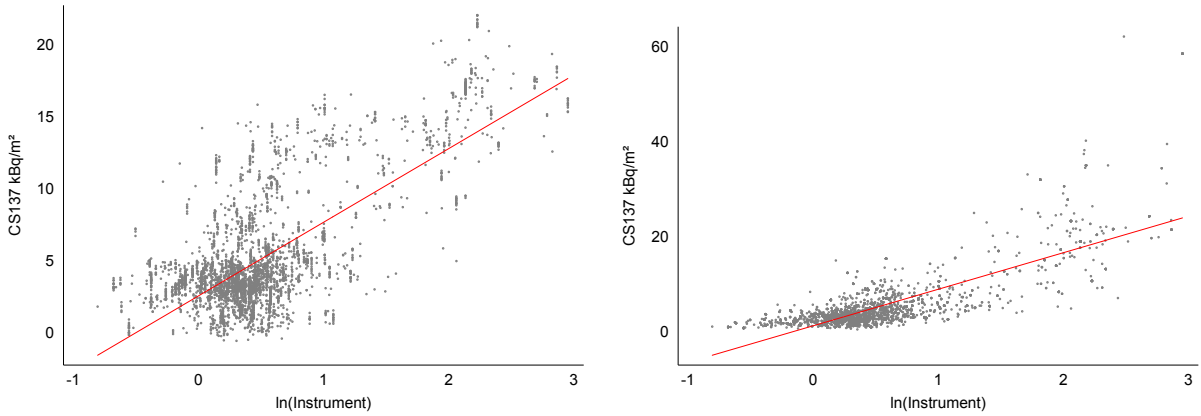
Identification While the instrument is constructed based on the actual rainfall $rain_m^{86}$ our identification relies on *unexpected* rainfall within a ten-day window. We isolate the unexpected component of rainfall by controlling for *expected* rainfall – the average in the period April 29-May 8 in the five years prior to the disaster – in both the first and second stage. The logic behind this identification strategy is that the level of unexpected rainfall and the amount of radioactive matter in the plume affect local fallout levels but are unrelated to residential sorting or other unobserved determinants of cognitive skills. Moreover, they should affect cognitive test scores only through local fallout but no other channel. We discuss these three assumptions – relevance, conditional independence and the exclusion restriction – in turn.

First stage and instrument relevance. In the first stage regression, we control for the same individual-, municipality- and county-level characteristics as in the OLS regression in Equation (1),

$$Cs137_{ims} = \lambda_0 + \lambda_1 \ln z_m + \boldsymbol{X'_{im}}\boldsymbol{\kappa} + \rho_s + \eta_{ims}. \tag{4}$$

Figure 3a provides preliminary evidence for the relevance of our instrument by showing

a positive raw correlation between the log of the instrument and the initial amount of Cs137 in 1986.[14] The regression line in Figure 3b represents the first-stage coefficient λ_1 in Equation (4), whereby the dependent variable is the level of Cs137 in a respondent's municipality in May 1986. Even after adding controls, the correlation is strong and has the expected positive sign. The F-Statistics for the instrument range between 30 and 66.[15]



(a) Raw correlation

(b) Correlation with controls

Figure 3: First-stage correlation

Notes: Panel (a) displays the first-stage correlation between the instrument $\ln(rain_m \times matter_m)$ and the amount of fallout Cs137. In Panel (b) we control for the indivdual, altitude an average rainfall as well as state fixed effects mentioned in Section 4.1. The graph plots the residuals with the means of both axes added in.

Instrument validity I: conditional independence. The first criterion for instrument validity is that – conditional on state fixed effects, average rainfall and altitude – the instrument is uncorrelated with determinants of cognitive skills. This assumption appears plausible given that we construct the instrument based on unexpected rainfall and we only consider a time window of ten days. Unexpected rainfall on a handful of days is unlikely to be systematically related to determinants of cognitive skills such as education decisions, parental inputs, or the decision to locate in a certain area. The balancing tests in Column (5) of Table 2 corroborate this assumption by showing that the instrument is uncorrelated with any individual characteristic, notably with one's own education as well as parental education.

[14] We choose the logarithm because of the non-linear relationship between rainfall and Cs137.

[15] See Table 4 for the first stage coefficients and F-Statistics for all regressions. The F-statistics vary because the size and composition of the sample differs between outcomes, which is a design feature of the survey. We show in Appendix B.5 that the participation in the surveys is uncorrelated with personal characteristics.

Instrument validity II: exclusion restriction. A further assumption for instrument validity is the exclusion restriction: the instrument should affect cognitive test scores *only* through its effect on local fallout but no other channel. Given that the instrument is based on rainfall, this assumption may warrant some skepticism. Studies have shown that rainfall often affects the outcome through more than one variable (Sarsons, 2015; Mellon, 2020). However, in our context, such a violation of the exclusion restriction appears unlikely. While determinants of cognitive skills such as parental inputs, income or educational inputs may be affected by rainfall in developing countries, the same appears implausible for Germany in the 1980s. For the vast majority of Germans, their economic situation does not depend on rainfall. Moreover, our instrument is based on unexpected rainfall within a short time window. It is hardly plausible that rainfall within such a short period of time would systematically affect any of these determinants. To corroborate the exclusion restriction, we provide empirical evidence based on the reduced form. In placebo regressions in Section 5.3, we construct the instrument based on rainfall on the same days in May in the years after the disaster. While we find a significant effect of the instrument based on rainfall in 1986, we find no effect in 1987 and 1988, when rainfall should not matter for cognitive skills.

4.4 Statistical Inference

To account for cross-sectional correlation in the error terms, we cluster the standard errors at the county-level, which is one geographic unit higher than municipalities. Clustering at this level allows for arbitrary correlations in the error terms within but not across countries. One concern may be that the error terms are spatially correlated across county borders, in which case we would under-estimate the standard errors. We address this concern in two ways. First, we perform a test of spatial autocorrelation based on Moran's I, which fails to reject the null hypothesis of no spatial autocorrelation.[16] Second, we also report standard errors at the state-level by using the cluster bootstrap-t procedure by (Cameron et al., 2008).

A further challenge is multiple hypothesis testing. The higher the number of hypotheses is to be tested, the greater is the likelihood of finding at least statistically significant effect. To address this problem, we estimate the effect of higher exposure on a standardized cognitive skills index, which is akin to a summary index test (O'Brien, 1984; Anderson, 2008), whereby we reduce the number of hypothesis tests from eight separate tests to one.

[16] After controlling for individual, municipality and county characteristics, Moran's I of the residuals with threshold distance 100km is $I = 0.001$, with a p-value of $p = 0.671$.

5 Radiation and Cognitive Skills: Results

5.1 Baseline OLS Results

Table 4 presents our baseline regression results. In Column (1), each coefficient is the result of a separate OLS regression of the outcome listed on the left on the level of Cs137 in May 1986, conditional on state fixed effects, individual and geographic controls. The outcomes are standardized to mean zero and standard deviation one, such that a coefficient of $\widehat{\beta} = -0.01$ means that an increase in Cs137 by 1 kBq/m^2 is associated with a decrease in the respective test score by 1% of a standard deviation. To facilitate the interpretation, we discuss the effect sizes relative to an increase in Cs137 by one standard deviation ($sd = 5.87$).

For four out of eight cognitive skills tests, the effects are large and statistically significant at the 10%-level or below. In Panel A, the effect sizes range between zero for logical reasoning and 8.2% of a standard deviation for reading comprehension. The most useful outcome for interpretation is the cognitive skills index, which summarizes the eight separate tests in Panel A. A one-standard-deviation increase in the initial level of Cs137 is associated with a decrease in the cognitive skills index by 4.7% of a standard deviation. Standardized to conventional IQ scores with mean 100 and standard deviation 15, this result is equivalent to a decrease by 0.7 IQ points. We find a slightly larger effect for tests based on crystallized intelligence relative to tests based on fluid intelligence, although the difference is not statistically significant.

In Appendix B.1, we also test for a non-linear dose-response relationship. Based on a polynomial regression, a spline regression and a level-log regression, we find little evidence of non-linear effects.

5.2 IV Estimates

Columns (2)-(5) of Table 4 present the components of the instrumental variable estimator from regressions with all controls and state fixed effects. In Columns (2) and (3) we report the first stage coefficients and corresponding F-statistics. Both differ across outcomes because the tests were taken by different, randomly selected subsamples. The first stages are sufficiently strong and the coefficients have the expected positive sign. The reduced form coefficients, shown in Column (4), lend further confidence to the IV results. While the magnitude is difficult to interpret, it is reassuring that we find negative and statistically significant coefficients for the same outcomes as in the OLS regressions in Column (1). It is, therefore, unlikely that the IV estimates result from a spurious first stage that is driven by sampling variation.

Table 4: The effect of radiation on cognitive performance – OLS and IV results

	OLS	IV			
		First stage	F-statistic	Reduced form	IV-2SLS
	(1)	(2)	(3)	(4)	(5)
A. Individual test scores					
Math	-0.011***	6.211***	66.2	-0.134**	-0.021**
	(0.003)	(0.041)		(0.058)	(0.010)
Reading	-0.013**	6.245***	46.1	-0.171***	-0.029***
	(0.006)	(0.086)		(0.040)	(0.008)
Listening comprehension	-0.009**	6.358***	57.9	-0.059	-0.010
	(0.004)	(0.048)		(0.048)	(0.008)
ICT	-0.005	6.611***	32.3	-0.025	-0.005
	(0.004)	(0.045)		(0.040)	(0.006)
Scientific literacy	-0.003	6.637***	33.2	-0.033	-0.004
	(0.003)	(0.047)		(0.040)	(0.006)
Reasoning	-0.000	6.256***	57.8	-0.038	-0.006
	(0.004)	(0.047)		(0.045)	(0.007)
Reading speed	-0.008*	6.103***	47.4	-0.115**	-0.017**
	(0.004)	(0.046)		(0.051)	(0.008)
Perceptual speed	-0.004	6.255***	63.7	-0.009	-0.001
	(0.003)	(0.046)		(0.046)	(0.007)
B. Indices					
Cognitive skill index	-0.008**	6.424***	43.7	-0.091**	-0.011**
	(0.003)	(0.035)		(0.037)	(0.006)
Crystallized intelligence index	-0.008**	6.710***	40.1	-0.095***	-0.014**
	(0.004)	(0.036)		(0.036)	(0.006)
Fluid intelligence index	-0.005	6.340***	58.1	-0.044	-0.008
	(0.003)	(0.039)		(0.039)	(0.006)

Notes: This table displays the OLS and IV results for the effect of initial exposure to Cs137 on cognitive performance. Column (1) reports the OLS estimates from separate regressions of the test scores on the left on the level of Cs137 in 1986. In all regressions we control for the individual characteristics described in Section 4.1, as well as average rainfall 1981-1985, altitude and state fixed effects. Columns (2) and (3) report the first-stage coefficients of Cs137 regressed on the instrument, controls and fixed effects, along with the corresponding F-statistics, respectively. Column (4) reports the reduced-form coefficients of separate regressions of the outcomes on the instrument, controls and fixed effects. The main IV results are displayed in Column (5). Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

The IV estimates in Column (5) confirm the OLS results in Column (1). Again, we find negative effects that are economically and statistically significant. For a one-standard-deviation increase in the initial level of Cs137, the effect sizes range between close to zero (perceptual speed) and a reduction in test scores by 16% of a standard deviation (reading comprehension). The effect on the cognitive skill index is -7.6% of a standard deviation, which is equivalent to a reduction by 1.1 IQ point.

We primarily view the IV estimates as a confirmation that our OLS estimates represent a causal effect. Although most of the IV coefficients are larger in absolute value, they are statistically indistinguishable from their OLS counterparts. This applies in particular to the overall cognitive skill index, which approximates the effect of radiation on the latent factor cognitive skills. The OLS estimate $\widehat{\beta^{OLS}} = -0.008$ is similar to the IV estimate $\widehat{\beta^{IV}} = -0.011$.

5.3 Robustness

Placebo IV regressions. To corroborate the validity of the instrument, we perform placebo tests based on the reduced form. We construct the instrument based on rainfall on the same days in late April and early May in 1987 and 1988. If we found significant coefficients in years other than 1986, this could indicate that our instrument picks up unobserved determinants of cognitive skills. Reassuringly, the reduced-form coefficients in Table C.8 show no significant relationship in the years after Chernobyl.

Data linkage. One concern is that the results are sensitive to the data linkage procedure. We link radiation and survey data via the centroid of a municipality, although a person may have lived in a different location within a municipality and, therefore, been exposed to a different radiation level. In Appendix B.2, we show that our estimates are robust to alternative linkage procedures.

Attrition: non-participation and mortality. Another concern is that the results are influenced by systematic non-participation in the cognitive tests. The tests in Appendix B.5 suggest that this concern is unwarranted. In Appendix B.4, we also show that our results are not driven by attrition through selective mortality.

Clustering of standard errors. In Appendix B.3, we address the concern that the clustering of standard errors at the county level may not be sufficient to account for spatial correlations in the error terms. In Table B.4 we report standard errors that are clustered at the state level. Because the number of state clusters is too small to allow for

reliable parametric inference, we apply a wild cluster bootstrap-t proposed by Cameron et al. (2008). The standard errors do not vary much across columns, highlighting the robustness of our inference.

5.4 Effect Magnitude and Discussion

The estimates presented in Table 4 show that the radiation induced by Chernobyl had significant negative effects on cognitive performance. A one-standard-deviation increase in ground deposition reduces cognitive test scores between 4.7% and 7.6% of a standard deviation, which is equivalent to 0.7-1.1 IQ points. With one percent of a standard deviation being roughly equivalent to the cognitive skills acquired in one school year, this means that receiving this additional radiation dose reduces a person's human capital by the equivalent of 5-10% of one school year.[17]

These effects appear economically significant when compared with the equivalent effective dose of other sources of radiation. Although the effective dose of the Chernobyl fallout is not straightforward to measure, estimates by the BfS suggest it is similar to the effective dose from medical procedures. The additional cumulative effective dose received by the average German over 25 years was around 0.6mSv, which is one-third of the effective yearly dose of background radiation (2mSv), or the equivalent of 30 chest x-rays. People in areas with higher contamination, for example Munich, received an effective dose of 2mSv, which is around the same as the dose from 150 chest x-rays or one CT scan of the head. Given that human cells react in a similar way regardless of whether a dose was received at once or over a longer period, our results suggest that low-dose radiation has an important effect on cognitive performance.

Another important benchmark are results from studies on in-utero exposure. The closest study for comparison is Almond et al. (2009). While their main specification is semi-parametric and, thus, difficult to compare, they also use the log amount of fallout in some regressions. In Table B.2, we estimate a similar specification and find that an increase in radiation by 100 log points reduced test scores by 9.2% of a standard deviation. The results in Almond et al. (2009) are significantly larger. They report an increase in math scores by almost 100% and an increase in overall GPA by 67.5% of a standard deviation. The effects found by Black et al. (2019) for Norway in the 1950s are considerably smaller. They report an effect between 2% and around 25% of a standard deviation.[18]

[17] The equivalence between cognitive performance and school years is based on a regression of years of education on the cognitive skills index using the main estimation sample, which yields a coefficient close to one.

[18] The effect sizes in Almond et al. (2009) refer to the effects of $log(CS137)$ at the municipality-level

These comparisons suggest that the effects of post-natal exposure are an order of magnitude smaller than the effects of exposure during pregnancy. This is hardly surprising; if cells are damaged while crucial body functions develop, the effects are more detrimental than after birth, when this process has been finished. Nonetheless, our effects are economically significant, not least due to the relative number of people exposed after birth. In West Germany in the 1980s, the number of people between weeks 8 and 25 of gestation at any point in time was around 200,000. On the contrary, the size of the birth cohorts 1956-1985 was 24 million.[19] Therefore, the in-utero studies document a very large effect of an environmental shock on a small number of people, whereas our paper documents a smaller effect for a population that is over 100 times larger.

5.5 Effects across Subgroups

In Table 5, we explore whether the impact of radiation exposure on cognitive performance differs between demographic groups. We base the analysis on OLS regressions because in interaction models the inference with OLS is less challenging compared to 2SLS regressions. In all regressions, the outcome is the standardized cognitive skills index. For each set of demographic groups, we interact Cs137 with mutually exclusive dummies for each group. For example, in Column (1), we interact the ground deposition with a dummy for male and a dummy for female, which yields separate estimates for both groups.[20] In all regressions, we control for individual characteristics, altitude, average rainfall as well as state fixed effects.

In Column (1), we find no difference in estimates between men and women. Despite potential differences between the two groups in daily routines, exercise habits and diets, we find the point estimates to be the same.

In Column (2), we consider differences between age groups. We generate mutually exclusive dummies for three groups based on the age in May 1986. We see significant negative effects for people who were age ten and over at the time of Chernobyl. This result confirms that radiation can have negative effects after early childhood and shows that the average effects in Table 4 are not purely driven by early-childhood exposure.

reported in Table IV. The effect on math scores is -4.491, which is 96% of $sd(math) = 4.66$, reported in Table IX. The effect on GPA is -2.47, which is 67.5% of $sd(GPA) = 3.97$. Black et al. (2019) write on p. 24 of the NBER Working Paper version: 'Our log coefficients for IQ score are about -.04 for ground and about -.25 for air. These are approximately 2% and 12% of a standard deviation of the 25 dependent variables.'

[19] Source: vital statistics provided by Destatis.

[20] We choose this specification for the ease of interpretation. It should be noted that, despite the inclusion of mutually exclusive dummies, there is no problem with multicollinearity. This would only occur if we additionally included both indicators in the regression. With only one indicator included – in this case a female dummy – the parameters are identified.

Perhaps surprisingly, we find insignificant effects among people who were younger than 10 years. One potential explanation for this result could be avoidance behavior. Although we have no formal way of testing this, widespread anecdotal evidence suggests that after Chernobyl parents kept young children indoors for several weeks, when the concentration of airborne radiation was highest.

In Column (3), we test for differences with respect to socio-economic status by comparing the effects on people whose parents have an education below and above secondary school (*Realschule*). The effect for people with less-educated parents is almost three times as large as the effect for those with highly-educated parents. There are many possible explanations for this difference. People of lower socio-economic status may have a greater exposure if they are more likely to work physically or through differences in their lifestyle. They may also have less knowledge or be less receptive to information about the negative consequences of radiation, such that they engage less in avoidance behavior.

Finally, in Column (4), we assess if the effects differ between people who, in 1986, lived in the GDR versus West Germany. This comparison can be informative about the role of information, as people in the GDR only learned about the disaster with a significant delay. The coefficient for East Germany is more than twice that of the coefficient for West Germany, although it is statistically insignificant.

Table 5: Heterogeneous effects

	(1)	(2)	(3)	(4)
CS137 kBq/m^2 × male	-0.008*			
	(0.005)			
CS137 kBq/m^2 × female	-0.008**			
	(0.003)			
CS137 kBq/m^2 × Age in 1986(0-10)		0.004		
		(0.005)		
CS137 kBq/m^2 × Age in 1986(10-20)		-0.018***		
		(0.007)		
CS137 kBq/m^2 × Age in 1986(>20)		-0.006**		
		(0.003)		
CS137 kBq/m^2 × Parent(above secondary education)			-0.004	
			(0.005)	
CS137 kBq/m^2 × Parent(below secondary education)			-0.010***	
			(0.003)	
CS137 kBq/m^2 × West Germany				-0.007***
				(0.003)
CS137 kBq/m^2 × East Germany				-0.021
				(0.017)
Controls:				
Individual characteristics	Yes	Yes	Yes	Yes
Altitude	Yes	Yes	Yes	Yes
Average rainfall	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	4440	4440	4440	4440
R^2	0.22	0.23	0.22	0.22

Notes: Each column reports the result from a regression of the standardized cognitive skills index on a full interaction between the ground deposition of Cs137 and mutually exclusive group indicators. In all regressions, we control for individual and municipality characteristics, as well as state fixed effects. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

6 Conclusion

In this paper, we have shown that radiation – even at subclinical doses – has negative long-term effects on cognitive performance. Using an instrumental variable approach, we exploit plausibly exogenous variation in soil contamination in Germany after the Chernobyl disaster in 1986. Our main finding is that people exposed to higher radiation perform significantly worse in cognitive tests 25 years later; a one-standard-deviation higher exposure reduces test scores by the equivalent of 0.7-1.1 IQ points.

These findings have implications for research and policy. Most research focuses on the effects of pollution exposure very early in life, often during pregnancy. The predominant finding is that exposure to pollution at this critical stage of a person's development has severe negative consequences. In contrast, there is little evidence of the impact of exposure *after* early childhood. By revisiting the consequences of the Chernobyl disaster with newly released data on adults' cognitive skills, we show that the negative effects of pollution are not limited to exposure early in life. And while the effects of post-natal exposure are smaller than those of pre-natal exposure, they are economically significant, not least because the population exposed after birth was over 100 times larger than those exposed during the critical months of pregnancy.

For policy-makers, these results are important for at least two reasons. First, they show that nuclear power comes with a substantial negative externality. With its ability to supply vast amounts of energy at zero carbon emissions, nuclear power is often considered critical in combating climate change. Our study adds to the evidence that this advantage does not come at zero cost. Although Chernobyl is over 1,000km away from the German border, the disaster's negative consequences significantly affect the German population. Indeed, while disasters like Chernobyl are rare, they certainly occur – for example, the Fukushima disaster in 2011 – and if they occur they have serious negative consequences.

Second, more generally, our results suggest that radiation has a human capital cost. While it is impossible for people to escape exposure altogether – natural radiation is present everywhere on earth – there are ways to shield the population away from it. One example is is through the choice of medical procedures. Analyses in the medical literature suggest that one-third of all CT scans are unnecessary (Brenner and Hall, 2007). Another example is the choice of building materials, given that some building materials are better at shielding people away from natural radiation, although their price may be higher than that of conventional materials. Our results can inform the cost-benefit trade-off of such choices.

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Online Appendices

A Data Description

A.1 Sampling in the ALWA Subsample

As described in Section 3, our main data source is the ALWA subsample of the NEPS Adult Cohort (SC6). Here we provide more detailed information on the sampling procedure. ALWA was sampled in two steps. First, 250 municipalities were randomly sampled, and subsequently people were randomly sampled within municipalities. To make the sample representative, the number of people sampled within a municipality was proportional to the total population of the cohorts born between 1956 to 1986. Within municipalities, people's addresses were randomly sampled from person registers. This procedure resulted in a sample of 42,712 addresses, for which telephone numbers were collected. The telephone number of 22,656 people could be identified, and prospective participants were contacted by phone. Out of these, 10,404 actually completed the interview between August 2007 and April 2008, which corresponds to a response rate of 24.4% out of all sampled addresses, and 45.9% of all sampled telephone numbers.

Before receiving the first call attempt, participants were sent information material about the study. Furthermore, to increase the willingness to participate, material incentives were provided; among all participants, 60 prizes such as laptops, travel vouchers or iPods were distributed through a lottery (Antoni et al., 2011). Computer-assisted telephone interviews (CATI) were used to collect information about current personal characteristics and about past events regarding residential, occupational and educational history.

To collect the residential information, interviewers asked participants to state the name of their municipality of residence. If a person lived abroad, the name of the country of residence was collected. Municipality lists were provided to interviewers to ensure a precise assignment of municipalities. In cases where municipality names were identical, interviewers asked about the county or federal state. Municipality keys were assigned by the interviewer based on the definition of 2004, although for the current NEPS datasets

the municipality keys have been transformed to the definition of 2013.

To minimize recall problems, the interviewers used a survey technique called True-Tales, which enhances respondents' memory based on the interconnection of modularized self-reports and event history calendars (EHC) (Reimer and Matthes, 2007). Key to this technique is that participants go through each domain of their life history – education, residence and work – separately. The interview process does not follow a continuous time line, but is rather based on events in a person's history, such as going to school, finishing college, or getting married. This procedure enhances participants' autobiographical memory. In addition, interviewers used a computer software that highlighted spatial as well as chronological inconsistencies between the three domains (Drasch and Matthes, 2013).

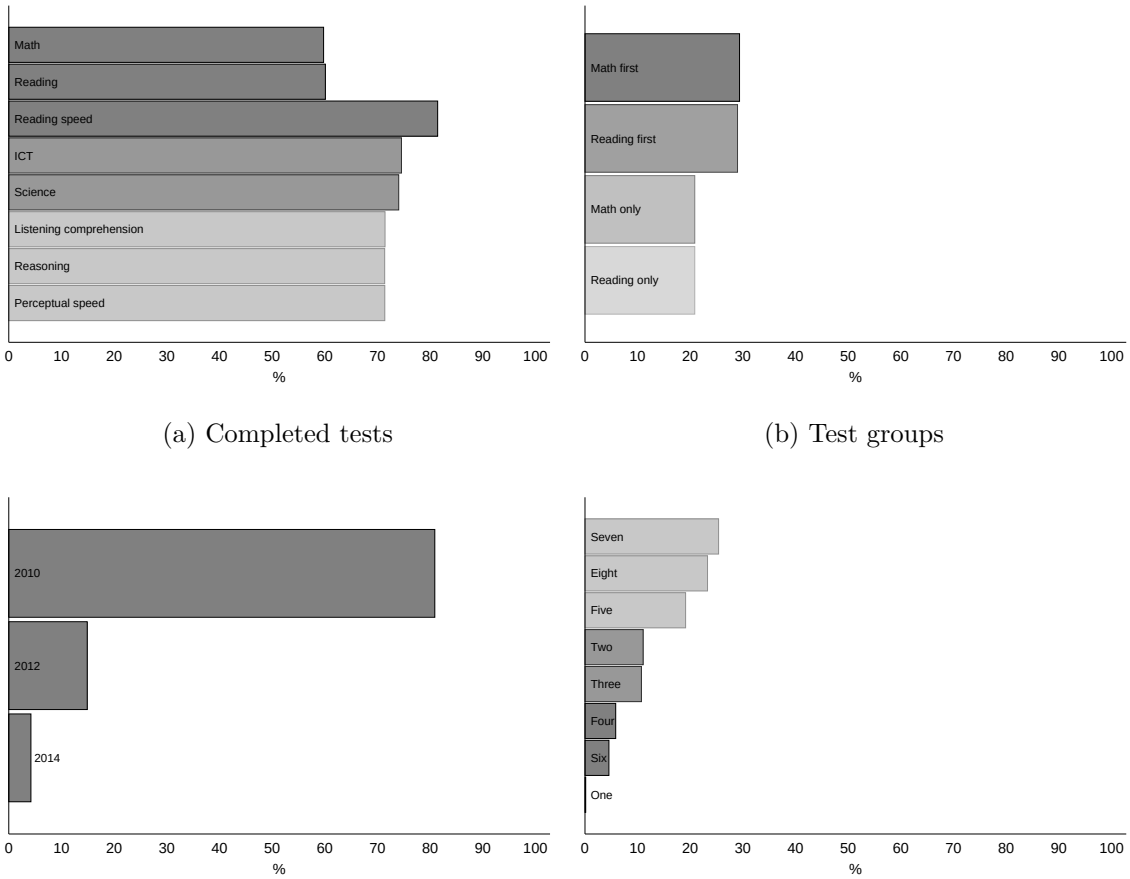
Each life history module starts with a respondent's birth and further goes through their lives. In the case of residential history, participants stated the current name of the municipality the residence was located in. Participants could state the municipality of their primary and secondary residency, although we only focus on the primary residence. In the education module, participants were asked to state the place and the type of educational institution they attended during a given spell. The employment module contains information about the employer, such as the location or sector, as well as contractual details such as the type of employment, income and working hours.

A.2 Participation in the Competence Tests

The tests were administered in three test periods between October 2010 and March 2015, namely tests in reading speed, math and reading between October 2010 and Mai 2011, tests in ICT and scientific literacy between October 2012 and April 2013, and tests in perceptual speed, listening comprehension and reasoning between August 2014 and March 2015. Most participants took their first test in the first test period, although, as illustrated in Figure 4c, some only started in the second and some few only in the third period.

As shown in figure 4b people were assigned to four different test groups which de-

termined the test order. The test groups were created to decrease panel attrition by lowering participants' workload. In addition, the different test sequences ensure that the test results are not driven by the order in which the tests are administered. While the test order in the last period (2014/2015) was the same for all groups, it differed in the first two test periods in 2010/2011 and 2012/2013. Some test groups skipped one or more tests altogether. For example, reading was skilled in the third and math in the fourth test group.



(a) Completed tests

(b) Test groups

(c) Year of first test

(d) Number of tests completed

Figure 4: Participation in cognitive tests

Notes: This figure displays descriptive statistics about the participation in cognitive tests for all 4,440 participants in our sample. Due to the survey design, not all participants took all tests, and tests were taken in different sequences. Panel (a) reports the share of participants who took a particular test. Panel (b) reports the distribution of test groups. Panels (c) and (d) show the distribution across years in which the first test was taken (left), as well as the number of tests taken by each participant (right).

Figure 4a shows that participants do not necessarily perform all tests. The numbers

of people completing a test varies between 2,644 (math test) and 3,602 (reading speed test). Overall, 4,423 participants performed at least one test. Figure 4d shows that most people completed at least seven tests, although a small number only performed one test. This difference in the number of tests completed is mainly due to the random assignment of people to tests. It is a design feature of the survey that not every participant had to complete all tests.

According to Aust et al. (2011), some participants refused to participate in competence tests. This was especially true for less educated participants. Furthermore, older people refused participation more often. In Appendix B.5, we test whether the non-participation in the competence tests is systematically linked to the level of radiation, which is not the case.

A.3 Variable Description

Table A.1: Variables and Data Sources

Variable	Description
A – Individual-level Variables in NEPS	
Age in 1986	Continuous variable of participants' age in May 1986.
Female	Dummy variable of participants' gender: 1) Female 0) Male
GDR	Dummy variable of participants' country of birth: 1) German Democratic Republic 0) Federal Republic of Germany

continued

Table A.1 continued

Variable	Source
Unemployed in April 1986	Dummy variable of participants' unemployment status in April 1986: 1) Unemployed 0) Employed
Employed in April 1986	Dummy variable of participants' employment status in April 1986: 1) Employed 0) Unemployed
Not of school age yet (less than 7 years old)	Dummy variable of participants' enrollment status in April 1986: 1) Below 7 years old and not enrolled 0) 7 years old and above
No degree, lower secondary, secondary	Dummy variable of participants' educational achievements in April 1986 who are not enrolled but older than six years: 1) No degree, lower secondary, secondary 0) Others
Upper secondary	Dummy variable of participants' educational achievements in April 1986 who are not enrolled but older than six years: 1) Upper secondary 0) Others
Tertiary	Dummy variable of participants' educational achievements in April 1986 who are not enrolled but older than six years: 1) Tertiary 0) Others

continued

Table A.1 continued

Variable	Source
In school or college education	Dummy variable of participants' educational activity in April 1986 who are older than six years: 1) Enrolled 0) Not enrolled
No degree	Dummy variable of participants' educational achievement in April 1986 who are older than six years and enrolled: 1) No degree 0) Others
Already attained lower secondary, secondary	Dummy variable of participants' educational achievement in April 1986 who are older than six years and enrolled: 1) Lower secondary, secondary degree 0) Others
Upper secondary	Dummy variable of participants' educational achievement in April 1986 who are older than six years and enrolled: 1) Upper secondary 0) Others

continued

Table A.1 continued

Variable	Source
B – Municipality-level Variables	
Caesium137 kBq/m^2 (01. May 1986)	Continuous variable of the ground radiation of Caesium137 kBq/m^2 at the municipality of residence in 01. May 1986. We computed this variable for the municipality centroid based on the inverse-distance weighted average of the four closest measuring points. Source: Federal Office for Radiation Protection
Average Caesium137 kBq/m^2 (until 2010, decay corrected)	Continuous variable of decay corrected Caesium137 kBq/m^2 levels at the municipality of residence between 1986 and 2010. Decay formula: $Cs137_t = Cs137_0 \times e^{-0.024t}$, Source: Federal Office for Radiation Protection
Precipitation mm/m^2 (yearly average, 1981-1985)	Continuous variable of precipitation in mm/m^2, computed for the centroid of a municipality based on the inverse-distance weighted average of the four closest measuring points. Source: German Meteorological Service

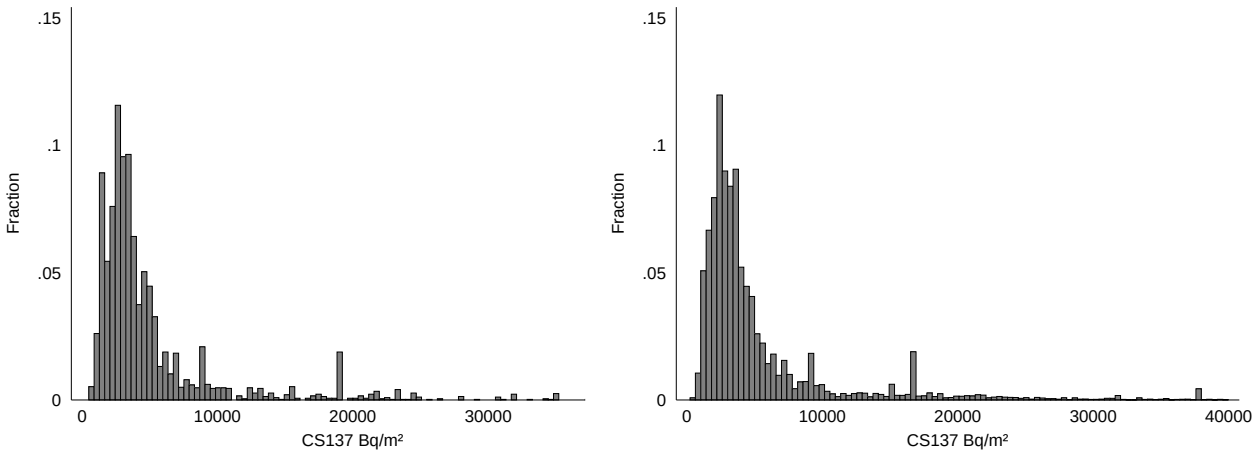
continued

Table A.1 continued

Variable	Source
Altitude in meter	Continuous variable of the municipality center's altitude. Source: Federal Agency for Cartography and Geodesy

A.4 Distribution of Fallout

Figure 5 displays the distribution of the fallout in our sample as well as the German population. Based on participants' municipality of residence in May 1986, Panel (a) displays the the ground deposition of Cs137 in Bq/m^2 for the sample. Panel (b) shows the corresponding distribution for the entire German population, which we obtain by weighting the ground deposition in each municipality with the population in 1997. This was the first year for which consistent population data are available for the municipalities based on the same definition as the one used by the NEPS.



(a) Sample

(b) Population

Figure 5: Variation in the ground deposition of Cs137in May 1986

Notes: This graph displays the distribution of the potential exposure to radiation, measured by the ground deposition of Cs137 in a person's municipality of residence in May 1986. Panel (a) displays the distribution in our sample, whereas Panel (b) displays the distribution in the German population. To obtain the distribution in the population, we computed the average ground contamination by municipality in 1986 and weighted the distribution by the population of each municipality in 1997. Sources: Federal Office for Radiation Protection (Bundesamt für Strahlenschutz) and The Service Center of the Federal Government for Geo-Information and Geodesy.

Table B.2: Non-linear effects

	(1)	(2)	(3)	(4)
CS137 kBq/m^2	-0.008***	-0.015**		-0.043
	(0.003)	(0.006)		(0.034)
CS137 kBq/m^2 $\times$ CS137 kBq/m^2		0.000		
		(0.000)		
ln(CS137 Bq/m^2)			-0.092***	
			(0.030)	
CS137 kBq/m^2 $\times$ above median				0.037
				(0.035)
Controls:				
Individual characteristics	Yes	Yes	Yes	Yes
Altitude	Yes	Yes	Yes	Yes
Average rainfall	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	4440	4440	4440	4440
Adj R^2	0.22	0.22	0.22	0.22

Notes: This table displays the estimates from OLS regressions of the standardized cognitive skill index on several functional forms of the ground deposition of Cs137 as well as the control variables listed at the bottom. See Section 4 for a detailed list of control variables. In Column (4), the ground deposition of Cs137 is interacted with an indicator that equals unity if a person lived in May 1986 in an area with an above-median ground deposition. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

B Robustness Checks and Additional Results

B.1 Non-linear Effects

In Table B.2, we analyze if there is a non-linear dose-response relationship between radiation exposure and cognitive test scores. In each regression, the outcome is the cognitive skills index. For comparison, Column (1) reproduces the linear estimate reported in Column (4) of Table 4.

The estimates in Columns (2) and (4) provide little evidence in favor of a non-linear relationship. In Column (2), we impose a quadratic relationship, but find no significant coefficient for the quadratic term. In Column (4), we estimate a spline regression by interacting the ground deposition with a binary indicator that equals unity if a person lived in 1986 in an area with above-median ground deposition. While the point estimate is larger for people living in areas with above-median ground deposition, the coefficient is statistically insignificant, such that a linear relationship cannot be rejected. In Column (3), we impose a log-linear relationship, for which we find a large and statistically significant coefficient. For a one-standard-deviation increase in the log ground deposition (sd=0.72), we find a decrease in cognitive test scores by 5.6% of a standard deviation, which is similar to the estimate from the linear level-level model in Column (1).

While the level-level model in Column (1) and the level-log model in Column (3) have a similar fit, a level-level model is more appropriate from a scientific standpoint. Radiobiology provides theories of a linear relationship between radiation exposure and the likelihood of a cell being damaged that have been verified in a series of experiments (Brenner et al., 2003). To the extent that our estimate is explained by the damage of brain cells or other cells in the body, it is plausible that radiation has a linear effect on test scores, which is why we use a linear model as our main specification.

B.2 Robustness to Different Data Linkage Procedures

To generate our main regressor of interest, the amount of ground deposition in Cs137 in May 1986 in a person's municipality of residence at the time, it is necessary to link the radiation data with the survey data based on assumptions. While we have fine-grained data on Cs137 at a 3x3km grid-cell level, we only know a person's municipality of residence rather than the precise coordinates of their place of residence. In addition, the cell-level data have been generated by the BfS based on an inverse-distance-weighted average of the four closest measuring points. In our main analysis, we link the radiation data via the geographic center (centroid) of each municipality. Both the interpolation by the BfS as well as the linkage via the centroid are potential sources of measurement error. Although we are unable to fully eliminate the measurement error, we can assess the robustness of our results to the choice of linkage procedure. In Table B.3, we re-estimate the baseline model from Table 4, Column (8), with regressors based on different data linkages. The results in Table B.3 strongly reject the notion that the results are driven our choice of linkage procedure.

- Column (1): baseline linkage, based on the inverse-distance-weighted average radiation of the four closest measuring points, linked via the municipality centroid
- Column (2): based on the radiation at the closest measuring point, linked via the municipality centroid
- Column (3): based on the inverse-distance-weighted average radiation of the four closest measuring points, linked via the population center of a municipality[21]
- Column (4): based on the radiation at the closest measuring point, linked via the population center of a municipality

[21] We computed the population center as the balancing point of a municipality based on night light data from 1996 provided by NASA.

- Column (5): based on the inverse-distance-weighted average radiation of the four closest measuring points, linked via the population mode of a municipality[22]
- Column (6): based on the radiation at the closest measuring point, linked via the population mode of a municipality
- Column (7): based on the unweighted average radiation in the entire municipality
- Column (8): based on the population-weighted average radiation in the entire municipality[23]

B.3 Alternative Clustering of Standard Errors

Table B.4 displays the 2SLS estimates from Table 4 with three types of clustering. In Column (2), the standard errors are parametrically estimated without any clustering. Column (3) reports the same standard errors as in Table 4, clustered at the county level. To address the concern that clustering at the county level is insufficient because error terms may be correlated across county boundaries, we report standard errors clustered at the state level in Column (4). Because of the small number of states, parametric estimation of standard errors can be misleading, which is why we estimate the standard errors non-parametrically using the bootstrap-t method by Cameron et al. (2008).

B.4 Testing for Selective Mortality

One important potential source of sample selection is selective mortality. Simply put, if radiation led to higher mortality among certain parts of the population, this population would be under-represented in our sample. To assess the importance of selective mortality, we obtained data on annual cohort-specific mortality data at the county level from the life tables of the German Statistics Office (Destatis).[24]. We run the following regression:

[22]We take as population mode the point in a municipality with the highest light intensity in 1996.

[23]The averages in Columns (7) and (8) were computed based on the 3x3km grid-level data. construct the population weights, we used night light data from 1996.

[24]Such detailed data is only available from 1995 onwards.

$$m_{crst} = \alpha + \rho_{rt}\ Cs137_{crs} + \boldsymbol{X'_{cs}}\boldsymbol{\kappa} + \delta_s + \varepsilon_{crst}. \tag{5}$$

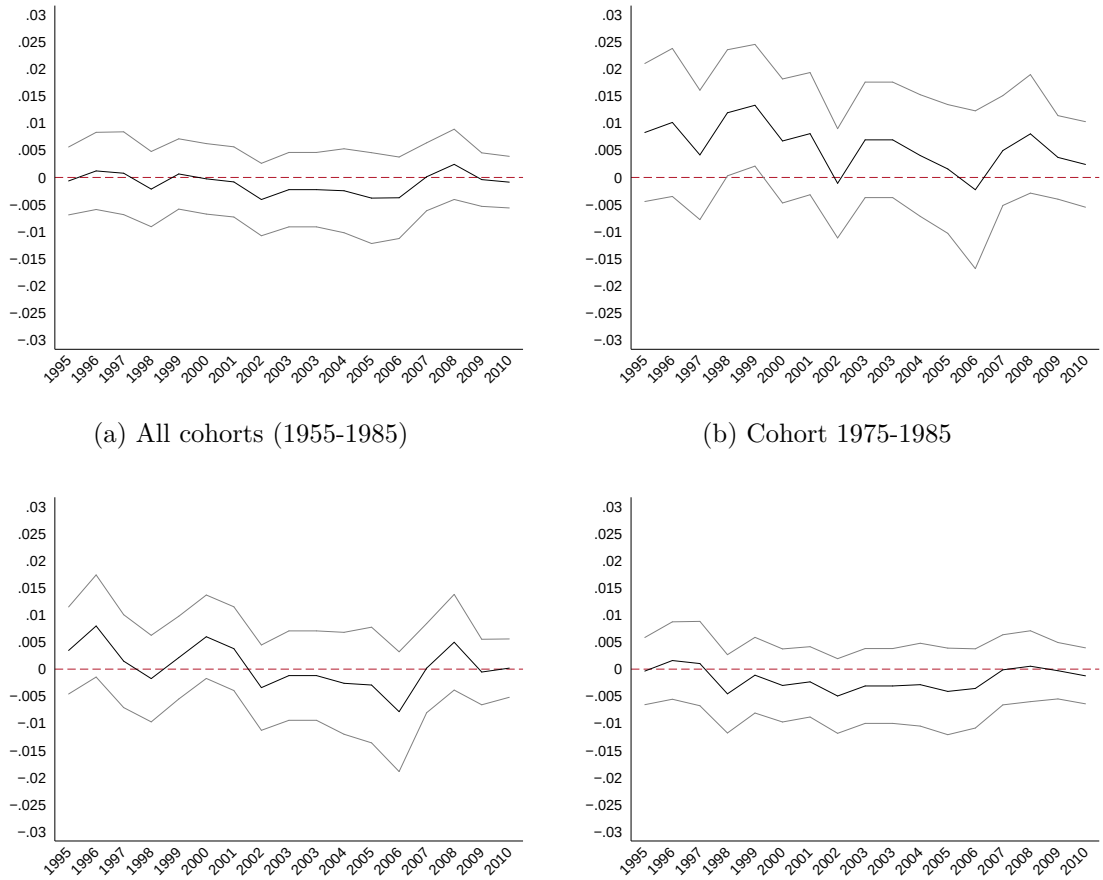
The number of deaths m_{cst} of age cohort r in county c state s in year t is regressed on the level of ground deposition of Cs137 in May 1986 in the same county. To obtain the level of ground deposition for each county, we match the radiation data based on the county centroid. The vector of controls, $\boldsymbol{X_{cs}}$, includes county characteristics, namely the level of rainfall altitude at the centroid and the total population in the country. In addition, we control for state fixed effects δ_s. The error term ε_{cst} summarizes all determinants of mortality not captured by the regressors. The coefficient ρ_r measures the reduced-form effect of exposure to radiation in April 1986 on mortality between 1995 and 2010.

Figure 6a displays the estimates ρ_{rt} for all cohorts, while the remaining Figures present cohort-specific estimates. We find no evidence that exposure to the Chernobyl fallout led to higher mortality until 2010.

B.5 Testing for Design-based Attrition

As shown in the descriptive statistics in Table 1, not all respondents took part in all eight cognitive tests. This is mostly due to the random assignment of respondents into test groups, whereby some test groups skipped one or more tests. In addition, some respondents refused to take one or more tests. Such selection into competence tests could confound our results if systematically related to the ground deposition of Cs137. To test whether this is the case, we regress participation dummies (one if a person completed a test, zero if not) on Cs137 as well as the same controls as in our baseline regressions. As Table B.5 shows, there is no evidence of systematic attrition or non-response once we add appropriate controls.

In Table B.6, we provide additional evidence that observations with missing information are missing at random. In Panel A, the outcome is a dummy that equals unity if a person participated in at least one competence test. We regress this dummy on the



(a) All cohorts (1955-1985)

(b) Cohort 1975-1985

(c) Cohort 1965-1975

(d) Cohorts born before 1965

Figure 6: Radiation exposure and mortality.

Notes: This graph displays the estimated effect of radiation exposure on standardized mortality in a given year. Both radiation and mortality vary at the county level. In all regressions, we control for county-level characteristics as well as state fixed effects. The lines in each panel represent the point estimates and 95%-confidence intervals based on separate regressions for each year. Panel (a) presents the estimates of ρ_{rt} for all cohorts in our estimation sample. Panels (b), (c), and (d) display the estimates of ρ_{rt} for distinct cohorts.

level of Cs137 and in some specifications control for municipality characteristics and state fixed effects. The results strongly reject that non-participation in the competence tests is related to radiation exposure. In Panel B, we investigate whether non-response due to missing information is related to Cs137, but find no evidence. In Panel C, we test whether the random sampling of municipalities described in Appendix A was indeed random and therefore unrelated to the level of fallout. The results suggest that inclusion in the sample and the level of fallout are indeed unrelated.

B.6 The Cognitive Skills Index with Non-participation

Besides looking at the effect of radiation on separate cognitive tests, we also consider its effect on a cognitive skill index, which combines all eight test scores. To produce our baseline results, we computed the index regardless of the number of tests a person actually completed. This means that for some respondents the index is based on all eight test scores while for others it is based on just one. To assess whether the results are driven by non-participation, we re-estimate the baseline regressions but restrict the sample to all participants who completed at least a certain number of tests. Table B.7 displays the results of this exercise. The coefficient in the first row is based on respondents who completed all eight tests, the coefficient in the second row is based on those who completed at least seven tests, the one in the third row is based on those who completed at least six tests, and so on. The coefficient in the last row represents our baseline estimate from Table 4, Column (8). The results show that, if anything, calculating the index based on all respondents leads to smaller estimates than calculating the index based on those who completed seven or eight tests.

Table B.3: Robustness to the data linkage procedure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Individual test scores								
Math	-0.011***	-0.009***	-0.012***	-0.010***	-0.014***	-0.012***	-0.013***	-0.012***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
Reading	-0.013**	-0.008**	-0.017***	-0.010**	-0.017***	-0.007	-0.016***	-0.015***
	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Listening comprehension	-0.009**	-0.005*	-0.009**	-0.006*	-0.007	-0.005	-0.012***	-0.012***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)
ICT	-0.005	-0.002	-0.007*	-0.004	-0.003	0.001	-0.006*	-0.006*
	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Scientific literacy	-0.003	-0.002	-0.005	-0.003	-0.003	-0.002	-0.005	-0.004
	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Reasoning	-0.000	0.001	0.001	0.002	0.002	0.001	-0.002	-0.002
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)
Reading speed	-0.008*	-0.005*	-0.011***	-0.004	-0.011**	-0.004	-0.010**	-0.009**
	(0.004)	(0.003)	(0.04)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Perceptual speed	-0.004	0.002	-0.005	-0.003	-0.004	-0.002	-0.005	-0.005
	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
B. Indices								
Cognitive skill index	-0.008**	-0.005**	-0.010***	-0.005**	-0.009**	-0.004	-0.010***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Crystallized intelligence index	0.008**	-0.005**	-0.011***	-0.007**	-0.010**	-0.004	-0.011***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Fluid intelligence index	–0.005	-0.003	-0.007*	-0.002	-0.006	-0.002	-0.007*	-0.007*
	(0.003)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Controls:								
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Altitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Altitude	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays the estimation results whereby the regressor has been constructed with different data linkage procedures. See text in Section B.2 for a description of the linkage procedures. The controls are the same as in Table 4, Column (4). Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table B.4: Estimates with cluster-bootstrapped standard errors

	Coeff	**SE**	**SE**	**SE**
	(1)	(2)	(3)	(4)
Method		Parametric	Parametric	Bootstrap-t
Level of clustering		none	county	state
A. Individual test scores				
Math	-0.021	(0.011)**	(0.010)**	(0.011)**
Reading	-0.029	(0.009)***	(0.010)***	(0.009)***
Listening comprehension	-0.010	(0.006)	(0.007)	(0.006)
ICT	-0.005	(0.006)	(0.006)	(0.005)
Scientific literacy	-0.004	(0.007)	(0.007)	(0.007)
Reasoning	-0.006	(0.004)	(0.005)	(0.005)
Reading speed	-0.017	(0.008)**	(0.008)**	(0.008)**
Perceptual speed	-0.001	(0.008)	(0.007)	(0.007)
B. Indices				
Cognitive skill index	-0.011	(0.006)**	(0.005)**	(0.006)**
Crystallized intelligence index	-0.014	(0.005)***	(0.005)**	(0.005)***
Fluid intelligence index	-0.008	(0.005)	(0.004)*	(0.005)
Controls:				
Individual characteristics	Yes	Yes	Yes	Yes
Altitude	Yes	Yes	Yes	Yes
Average rainfall	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Notes: Column (1) reproduces the IV point estimates of Column (5) in Table 4. Column (2) reports conventional standard errors. In Column (3) the standard errors are clustered at the county-level and have been computed based on the conventional parametric cluster-robust procedure. The standard errors in Column (4) are clustered at the state level and have been computed non-parametrically based on a wild cluster boostrap-t proposed by Cameron et al. (2008). Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table B.5: Selection into competence tests

	(1)	(2)	(3)	(4)
Math	-0.002	-0.002	-0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.000)
Reading	-0.000	-0.000	0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.000)
Listening comprehension	0.000	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
ICT	0.002**	0.003*	0.003**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Scientific literacy	0.002**	0.002*	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Reasoning	0.000	0.002	0.003*	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Reading speed	-0.001	-0.002	-0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.000)
Perceptual speed	0.000	0.002	0.003**	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Controls:				
County characteristics	No	Yes	Yes	Yes
Municipality characteristics	No	Yes	Yes	Yes
State FE	No	No	Yes	Yes
Individual characteristics	No	No	No	Yes

Notes: This table displays the results of separate regressions of dummy variables – indicating if an individual participated in the test or not – listed on the left on the ground deposition of Cs137, controlling for the variables indicated at the bottom. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table B.6: Attrition

	(1)	(2)	(3)
A. Participation in competence test			
Cs137 kBq/m^2	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
(N)	5844	5844	5844
B. Missing personal information			
Cs137 kBq/m^2	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.002)
(N)	4545	4545	4545
C. Municipality included in sample			
Cs137 kBq/m^2	0.0000	0.0004	-0.000
	(0.0002)	(0.0003)	(0.0003)
(N)	11197	11197	11197
Controls:			
Altitude	No	Yes	Yes
Average rainfall	No	Yes	Yes
State FE	No	No	Yes

Notes: This table displays the results of regressions of indicators for participation or attrition on the level of fallout in 1986. In Panel A, the dependent variable is a binary indicator that equals unity if a person participated in the competence test. In Panel B, the dependent variable equals unity if the person is excluded from the estimation sample due to missing personal information. In Panel C, the dependent variable is an indicator that equals unity if a municipality was included in the NEPS SC6 sample and has at least one observation. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

Table B.7: The cognitive skills index with different definitions

	(Coef.)	(N)
All eight tests	-0.012**	1034
	(0.006)	
At least seven tests	-0.012***	2159
	(0.004)	
At least six tests	-0.013***	2360
	(0.004)	
At least five tests	-0.009**	3207
	(0.004)	
At least four tests	-0.010***	3466
	(0.003)	
At least three tests	-0.011***	3942
	(0.003)	
At least two tests	-0.008**	4430
	(0.003)	
At least one test	-0.008**	4440
	(0.003)	
Controls:		
Individual characteristics	Yes	
Altitude	Yes	
Average rainfall	Yes	
State FE	Yes	

Notes: This table displays the results of regressions of the standardized cognitive skills index on the level of ground deposition of Cs137 and the controls listed at the bottom. In each row, we consider different sample definitions. In row one, the index is based on participants who completed all eight tests. In the second row, we consider all participants who completed at least seven tests, etc. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.

C Diagnostic Tests in Support of Instrument Validity

In Table C.8, we perform an additional set of diagnostic tests for the instrument validity by estimating the reduced form based on rainfall in different years. Ideally, we only want to find significant reduced-form effects based on rainfall in early May 1986 but not based on rainfall on the same days in May in 1987 or 1988. Each coefficient is the result of a separate regression of the outcomes on the left on the instrument, individual-level controls, controls at the municipality- and county-level and state fixed effects. Column (1) displays the reduced form based on rainfall in 1986. All coefficients have the expected negative sign and 5 out of 11 coefficients are statistically significant at the 5%-level. In Columns (2) and (3) we estimate the same regressions but construct the instrument based on rainfall between May 1 and May 10, 1987 and 1988, respectively. Out of the 22 coefficients in both columns, two are significant at the 10%-level, which is consistent with random sampling variation. This indicates that the instrument works as it should. The assignment of the fallout is determined by rainfall while the plume was above Germany but not by rainfall on similar days in subsequent years.

Table C.8: Diagnostic tests based on reduced form

	1986 (1)	1987 (2)	1988 (3)
A. Individual test scores			
Math	-0.134**	-0.041	0.013
	(0.058)	(0.083)	(0.082)
Reading	-0.171***	0.008	-0.063
	(0.040)	(0.073)	(0.094)
Listening comprehension	-0.059	0.086	0.027
	(0.048)	(0.078)	(0.084)
ICT	-0.025	0.057	0.063
	(0.040)	(0.062)	(0.078)
Scientific literacy	-0.033	0.122	-0.053
	(0.040)	(0.082)	(0.077)
Reasoning	-0.038	0.127*	0.162*
	(0.045)	(0.077)	(0.096)
Reading speed	-0.115**	-0.005	-0.028
	(0.051)	(0.076)	(0.083)
Perceptual speed	-0.009	-0.041	0.021
	(0.046)	(0.071)	(0.071)
B. Indices			
Cognitive skill index	-0.091**	0.042	0.013
	(0.037)	(0.061)	(0.061)
Crystallized intelligence index	-0.095***	0.046	-0.040
	(0.036)	(0.068)	(0.086)
Fluid intelligence index	-0.044	0.024	0.032
	(0.039)	(0.034)	(0.065)

Notes: This table displays the coefficients of reduced-form regressions of the outcomes listed on the left on the instrument. In each column we construct the instrument based on rainfall between May 1 and 10 in the year listed at the top of the table. In all regressions, we control for individual, municipality and county characteristics, as well as state fixed effects. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***: p < 0.01$, $**: p < 0.05$, $*: p < 0.1$.