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Long-run exposure to low-dose radiation reduces cognitive performance☆

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ABSTRACT

This paper examines the effect of long-run exposure to low-dose radiation on cognitive performance. We focus on the fallout from the Chernobyl accident, which increased the level of ground radiation in large parts of Europe. To identify a causal effect, we exploit unexpected rainfall patterns in a critical time window after the disaster as well as the trajectory of the radioactive plume, 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. An increase in initial exposure by one standard deviation reduces cognitive test scores by around 5% of a standard deviation.

1. Introduction

The last 40 years have seen a drastic increase in radiation exposure. Today, the average person in Europe and America receives about twice the annual dose of radiation compared with in 1980 (NCRP, 2009). This increase is almost entirely due to man-made sources of radiation, such as medical procedures, nuclear power and nuclear weapons. Procedures such as CT scans, X-rays, mammograms or radiotherapy expose patients to low doses of radiation, and their use has been steadily increasing over the past decades. Moreover, the fallout from nuclear disasters such as Chernobyl and Fukushima or a nuclear bomb can expose people thousands of miles from the epicenter.

Medical research shows that subclinical radiation can damage human cells, which has potential knock-on effects on health and cognition and that these effects may occur at all ages. The existing literature has mostly focused on the effect of in-utero exposure, documenting significant adverse effects of radiation exposure during pregnancy on education and labor market outcomes many years later (Almond et al., 2009; Heiervang et al., 2010; Black et al., 2019). However, there is little evidence on the long-term effects of

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exposure to low-dose radiation after birth. Documenting such effects is important, not least because of the number of potentially affected people: the number of people alive at any one point is substantially greater than the number of fetuses in the womb.

In this paper, we exploit plausibly exogenous variation of the Chernobyl fallout to study the impact of exposure to low-dose radiation on cognitive test scores 25 years after the disaster. We focus on Germany, which received a significant amount of fallout due to weather conditions in the aftermath of the disaster in 1986. Because of the long half-life of the radioactive matter, people who continuously lived 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: a direct effect on the brain because radiation can damage brain cells, and an indirect effect through general health, which may lead to fatigue, thus reducing test performance.

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 since 1986 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 a potential correlation between the local amount of radiation and residential sorting. The local amount of radiation is driven by a combination of several factors, for example wind speed, rainfall, altitude or soil composition. Some of these factors may have also influenced residential sorting prior to 1986, thus potentially leading to omitted variable bias. For instance, if people with lower education levels tend to live at higher altitude and places at higher altitude received higher amounts of fallout, we may observe a negative correlation between fallout and cognitive skills that is entirely driven by residential sorting. 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 overcome the confounding influence of residential sorting, we first show that the local level of radiation is uncorrelated with a large number of observable characteristics. Moreover, to address concerns about sorting with respect to unobservable characteristics, we pursue an instrumental variable strategy that relies on two determinants of local fallout that are plausibly orthogonal to residential sorting or other determinants of test scores. One is the amount of local rainfall while the radioactive plume was over Germany. We capture the idiosyncratic component of local rainfall by controlling for the average amount of rainfall in a municipality in early May. The control breaks the correlation between rainfall and residential sorting, such that the remaining variation in rainfall is idiosyncratic — that is, it captures whether it rained more or less than usual around this time of 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 provide evidence that our controls and fixed effects capture a potential correlation between the trajectory of the plume and residential sorting that would otherwise invalidate the IV estimation.

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 idiosyncratic rainfall and (ii) we focus on a narrow time window of ten days after the disaster. We view it as unlikely and implausible that short-term fluctuations 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 later 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 around 5% of standard deviation. Over the course of 25 years, the additional radiation dose of a one-standard-deviation higher initial exposure is roughly equivalent to the dose from 6 chest X-rays or 1.65 mammograms, which indicates that the long-term effects of low-dose radiation can be non-trivial. An additional analysis shows that these effects are not driven by selective migration after the Chernobyl disaster.

This result feeds into two domains of the public debate on radiation. One is about the costs and 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. Given the proliferation of nuclear power along with the emergence of conflicts like the current war in Ukraine, it is possible that more nuclear disasters may follow. Our results, along with those in other studies, point to significant external costs of nuclear power generation and document an important effect of nuclear disasters on the population. 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 in 1980, which is mainly due to medical procedures such as X-rays, mammograms or CT scans (NCRP, 2009). Our results can inform the debate about the long-term consequences of this increase in radiation exposure. The radiation dose from medical procedures is similar to the additional radiation dose Germans in highly affected areas received after Chernobyl. And although these procedures offer high benefits for patients, our findings suggest that they come with a health cost due to a higher radiation exposure.

With this paper, we contribute to three strands of literature. First, our findings contribute to the literature on the effect of pollution on human capital. This literature has produced compelling results for two types of effects. One strand 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 adds new evidence to the emerging literature on pollution and cognitive functioning. Recent contributions by Ebenstein et al. (2016), Künn et al. (2023) and La Nauze and Severnini (2021), among others, have documented an immediate negative effect of exposure to fine particulate matter on cognitive performance. A longer-term perspective is provided by Bishop et al. (2023). They exploit variation in particulate matter induced by the Clean Air Act and show that higher exposure to particulate matter over many years increases the risk of dementia. Our work documents similar effects for radiation. Although we have no information on dementia, we show that exposure to radiation has negative long-run effects on cognitive performance.

Third, 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 1200 km from Chernobyl, and our study shows that large parts of the population have been adversely affected.

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.[2] 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).

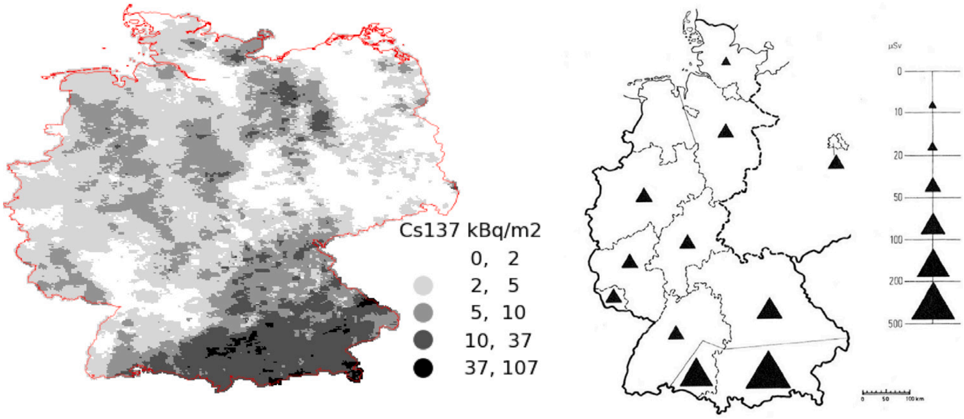
Post-Chernobyl radiation in Germany. The radioactive plume reached Germany three days after the disaster, on April 30, 1986. It first entered the country in the south-east and made its way north-west before disappearing over the North Sea on May 8. The fallout comprises four main isotopes, namely caesium-137 (Cs137), caesium-134 (Cs134), strontium-90 (Sr90) and iodine-131 (I131), which have half-lives of up to 30 years.[3] 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.

Fig. 1(a) 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.

[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, 2019) 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), and Schlenker and Walker (2011), Mullins and Bharadwaj (2015) (health).

[2] 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 1000 Bq.

[3] 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.



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

Fig. 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.).

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 be 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 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 radiation dose most people received from the Chernobyl fallout can be considered *low-dose* radiation, that is, a radiation dose that is not uncommon and does not require immediate medical attention. The cumulative effective radiation dose induced by Chernobyl – the total dose that entered the tissue of an average person – was 0.6 mSv, which is comparable to the dose from 6 chest X-rays or 1.5 mammograms.[4] The BfS estimates that in 2022 the average German person receives an annual dose of 0.7 mSv from external exposure, that is, through natural background variation, 1.1 mSv from inhaling radon and 0.4 mSv from ingesting radionucleids (BfS, 2019). This means that the cumulative radiation dose from the Chernobyl fallout for the average German was similar to the annual dose from background radiation. However, the doses from Chernobyl significantly varied across regions. In Munich, one of the more affected cities, the cumulative effective dose was 2.1 mSv, which is equivalent to the total annual radiation dose of the average German or the radiation dose of one CT scan of the head (BfS, 2016).

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.

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

[4] For average estimates of effective doses of radiation, see Mettler et al. (2008). Average effective doses: panoramic dental X-ray (0.01 mSv), chest X-ray (0.1 mSv), mammogram (0.4 mSv), CT scan of head (2 mSv)

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.

While the German population was generally informed about the radioactive fallout, they had little knowledge about the levels of fallout in particular areas. Fig. 1(b) 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 Fig. 1(a) 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.[5]

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). Importantly, though, the effective dose from radiotherapy is considerably larger than the average cumulative effective radiation dose received by the German population after Chernobyl. Uselmann and Thomadsen (2015) present estimates for effective doses of radiotherapy patients around 300 mSv, which is 500 times larger than the average effective dose from Chernobyl, which is 0.6 mSv.

[5] It is possible that behavioral responses are amplified through peer effects. If one person changes their behavior in response to radiation exposure, this may induce behavioral changes in their peers. Our reduced-form estimates will incorporate this channel along with many other potential behavioral responses.

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.

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, 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.

ALWA was sampled in two steps. First, 250 municipalities were randomly sampled from all German municipalities, and subsequently people were randomly sampled from within the included 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.

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

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 at least one competence test (1,265 obs.), as well as all participants for whom information on personal characteristics is missing (105 obs.). After applying these restrictions, our final estimation sample comprises 4,440 observations from 198 municipalities. page:nrmuni The average municipality has 22 observations in the sample, with the number of observations per municipality ranging between one and 155.,[8]

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. We also show in Appendix B.14 that there is no systematic relationship between Cs137 and the fact that a municipality is represented in the estimation sample. In Appendix A.5, we provide more detailed information on the municipalities represented in the estimation sample.

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 (information and communications technology)* , *reading speed*, *perceptual speed*, and *reasoning*. Although each test measures a different dimension of cognitive skills, the test scores are correlated, with correlation coefficients ranging between 0.22 and 0.64 (see Appendix A.3 for more details).

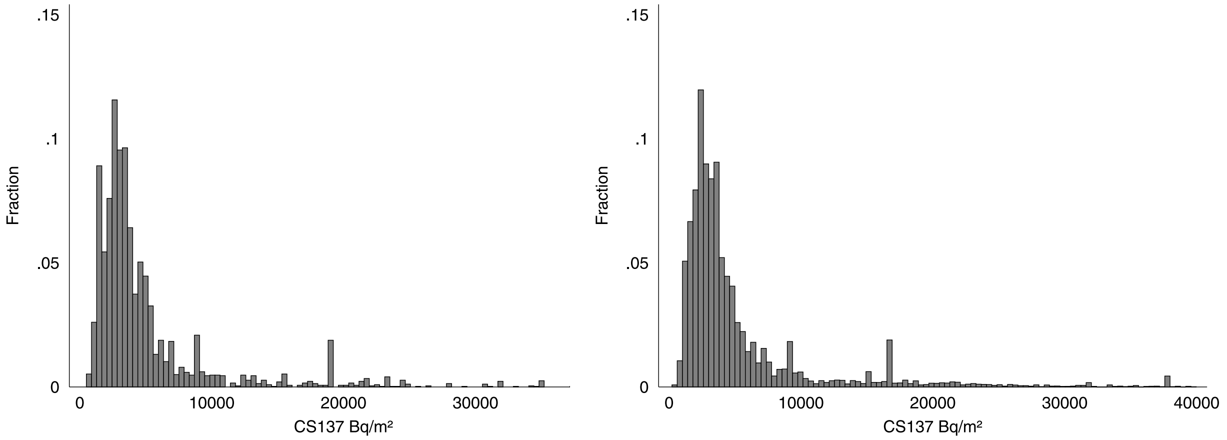
The tests were administered in three test periods between October 2010 and March 2015, namely tests in reading speed, math and reading comprehension between October 2010 and May 2011, tests in ICT and scientific literacy between October 2012 and April 2013, and tests in perceptual speed, listening comprehension and reasoning between August 2014 and March 2015. The test protocol was set up in such a way that (i) not every participant was asked to participate in all eight tests – thereby reducing the participants' workload – and (ii) participants were randomly assigned to the sequence in which they took the tests — which avoids that the test results are not driven by the order in which the tests are taken. This means that not all participants took all the tests by design, plus there was some attrition and non-participation. 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.

Table 1 below shows that in our estimation sample the tests were taken by between 2,652 and 3,611 participants. In Appendix A.2 we provide more details on the distribution of the number of tests taken per participant. For example, we show that most participants completed seven or eight tests, and there were few participants who only completed between one and four tests. In Appendix B.14, we test whether the non-participation in the competence tests is systematically linked to the level of radiation, which is not the case. Moreover, in Appendix B.9, we perform robustness checks whereby we exclude all participants who completed a small number of tests.

In the empirical analysis, we use each test score as a separate outcome. In order to make the estimates comparable across outcomes, we standardize each test score 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 for each respondent by taking the sum over all eight standardized test scores and standardizing this sum to a mean of zero and a standard deviation of one. Although this index is standard in the literature (e.g. Kling et al., 2007), one potential challenge is that not every participant took every test, which could mean that it mechanically increases with the number of tests a respondent has taken. In Appendix B.8, we show that the index is unrelated to the number of tests. Moreover, we perform a robustness check with an index based on the average rather than the sum of standardized test scores.

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

[8] In Appendix A.5, we show a histogram with the distribution of observations per municipality.



(a) Sample

(b) Population

Fig. 2. Variation in the ground deposition of Cs137 in 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.

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 for West Germany were compiled by the BfS following a comprehensive measurement program rolled out between 1986 and 1989. For East Germany, the data were collected shortly after the reunification. Measurements taken after May 1986 were backdated based on the decay of Cs137. In our estimation sample, most municipalities had one or two measuring stations (170 out of 198). Eight municipalities had no measuring station, whereas another 20 municipalities had more than two measuring stations..[9]

For each municipality centroid, we calculate the radiation level as the inverse-distance weighted average from the four closest measuring points.[10] 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.

Fig. 2 displays the distribution of Cs137 in our estimation sample (Panel (a)). Most respondents resided in municipalities with a ground deposition between 0 and 10 kBq/m^2, although there is a considerable right tail of respondents who were exposed to higher doses. For comparison, Panel (b) displays the same distribution for the German population. The similarity of both panels suggests that the estimation sample is representative of the population in terms of radiation exposure.

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 starting in May 1986, using the radiation level in the centroid of the municipality. As our preferred measure for radiation, we use the inverse-distance weighted ground deposition of Cs137 based on the four closest measuring points. This procedure follows the standard practice by the BfS. This linkage provides us with a measure of potential exposure to the post-Chernobyl radiation for each person in the sample.[11] Because we link the data without knowing the precise

[9] For a histogram of the distribution of measuring points per municipality, please consider Appendix A.6.3.

[10] 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.7, we also run a robustness check wherein we calculate radiation levels based on the closest measuring point.

[11] 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.

place of residence within a municipality, the linkage inevitably introduces measurement error. We address this problem in several robustness checks in Appendix B.7, 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 noteworthy 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). The estimation sample comprises of 4,440 respondents who took at least one competence test, although not everyone took every test (see Section 3.3 and Appendix for more information on the tests).

Panel B displays the municipality-level characteristics. The statistics were computed across individual observations in the estimation sample.[12] 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. 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 3.89 kBq/m^2.

The level of precipitation represents the average local rainfall in May in the five years preceding the Chernobyl disaster, i.e.1981–1985. The two measures of altitude represent important determinants of radiation. They jointly determine orographic rainfall, which in turn affects the level of radiation after the disaster. The remaining statistics provide further information on municipality characteristics (population size and density, surface).

4. Empirical strategy

4.1. Empirical model

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

$$y_{i(ms)} = \alpha + \beta \ \mathrm{Cs137}^{86}_{m(s)} + \boldsymbol{X}'_{\boldsymbol{i(m)}}\boldsymbol{\gamma} + \delta_s + \varepsilon_{i(ms)}. \tag{1}$$

In the underlying thought experiment we compare people who are exposed to different doses of radiation because of where they lived at the time of the disaster. This set-up is akin to an experiment in which everyone is treated with a randomly assigned treatment dose. As such, it differs from a randomized experiment with a binary treatment where some units are treated and others not.

The outcome $y_{i(ms)}$ 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. We use the notation $i(ms)$ because the outcome varies at the individual level whereas some right-hand side variables vary at the level of municipalities or states.

The regressor $\mathrm{Cs137}^{86}_{m(s)}$ measures the *initial* level of exposure, and as such it reflects the potential – as opposed to the actual – exposure to radiation. Actual exposure is nearly impossible to measure because we would need to know the actual radiation dose a person's body has absorbed. Such information is very difficult to obtain, which is why studies typically focus on the potential exposure, that is, the amount of radiation in the place where a person lives or works.

[12] This means that if 100 respondents live in municipality A, this municipality gets a weight of 100/4440 because 4440 is the total sample size. We choose this weighting because this is the weighting applied in the regressions controlling for municipality characteristics.

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 Comprehension	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
Cognitive skill index	−0.00	1.00	−5.13	2.95	4440
B. Municipality-level data					
Caesium137 kBq/m^2 (01. May 1986)	5.18	5.87	0.50	62.10	4440
Average Caesium137 kBq/m^2 (until 2010, decay corrected)	3.89	4.41	0.38	46.64	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
Population/1000	281.67	676.43	5.00	3420.00	4440
Population density	1031.61	1731.13	21.00	4731.00	4440
Square kilometer	273.04	393.40	1.40	891.00	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, although the statistics themselves are computed at the individual level.

Because $\mathrm{Cs137}^{86}_{m(s)}$ reflects the *initial* level of exposure, the coefficient β is to be interpreted as an intention-to-treat (ITT) effect. The ITT effect reflects the total effect of a person's exposure over the entire sample period. People who lived in a municipality with higher radiation initially were also exposed to a higher level of radiation over the next 25 years — provided that they did not move. The ITT effect also comprises all channels through which the initial radiation exposure affects cognitive test scores, such as the direct effect on cognition as well as indirect effects through health or changes in behavior. A challenge with the ITT is that it does not allow researchers to separate the direct effect on cognitive performance from the indirect effect through selective migration after Chernobyl. To address this concern, we construct a person's average exposure over 25 years based on their residential history and provide alternative results based on this measure. Moreover, we test directly whether the initial radiation exposure is systematically related to migration.

In our most comprehensive specification, we control for pre-determined individual, county and municipality characteristics, which are summarized by the vector $\boldsymbol{X}_{i(m)}$. At the individual level, $\boldsymbol{X}_{i(m)}$ 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 as well as altitude, which are both important determinants of Cs137 and potentially correlated with residential sorting.[13] To capture features of 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.

[13] 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.4 provides further details on the control variables.

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.[14] 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 — Fig. 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 $\varepsilon_{i(ms)}$ summarizes all determinants of cognitive test scores that are not captured by the regressors. 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.[15] In robustness checks, we also test for spatial autocorrelation and report standard errors clustered at the state level based on the cluster bootstrap-t procedure by Cameron et al. (2008).[16] To address concerns about multiple hypothesis testing, we use as the main outcome a cognitive skill index, which reduces the number of hypothesis tests from eight separate tests to one.[17]

4.2. Identification challenge and balancing checks

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:

$$E[\varepsilon_{i(ms)}|\text{Cs137}_{m(s)}, \boldsymbol{X}_{\boldsymbol{i(m)}}, \delta_s] = 0. \tag{2}$$

Studies on the effect of pollution face two fundamental identification challenges, namely anticipation and residential sorting. People may avoid exposure if they can anticipate where the exposure is highest. Moreover, the determinants of local exposure may also determine residential sorting, thereby introducing a spurious correlation between radiation and cognitive skills.

In the case of Chernobyl, anticipation is implausible. People could neither foresee the 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 1,200 km away. Importantly, anticipation effects are to be distinguished from avoidance behavior in response to the disaster, such as internal migration or changes in lifestyle. Differently from 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.

In contrast, residential sorting is an identification challenge that is potentially important. The same factors that determine why people move to a particular place – weather, amenities, health, etc – may also determine the local level of fallout after the disaster. Regardless of the exposure to radiation, we are likely to observe differences in cognitive performance across space, for example between people living in large cities and more rural areas or between people living in places with different altitude. The identification of a causal effect of radiation on cognitive performance requires the elimination of residential sorting as a confounder. This is challenging because ideally one would need to control for all the determinants of residential sorting that may also affect cognitive performance, but some of these determinants are not known to us or are unobservable.

In Table 2, we assess whether the respondents' pre-determined characteristics show evidence of residential sorting. Each coefficient 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. Statistically significant coefficients would be an indication the variation in Cs137 is not as good as random and the assumption in Eq. (2) is violated. 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 control for confounding factors and condition on state fixed effects. In Column (4), when we condition on state fixed effects and control for altitude and average local 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.

In the final row, we test whether the number of tests a respondent has taken differs systematically by initial exposure to radiation. This appears not to be the case. Although the coefficient in Column (2) is statistically significant, all coefficients are close to zero. Moreover, the coefficient in Column (4), which is based on the identifying variation, is statistically insignificant and close to zero.

Overall, the balancing tests support the identification assumption in Eq. (2) by showing that sorting on observables is conditionally uncorrelated with the local level of fallout.[18]

[14] 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.

[15] Given that there are few counties with more than one municipality represented in the estimation sample, we also report standard errors clustered at the municipal level.

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

[17] Summarizing the outcomes in an index is often referred to as a *summary index test* (O'Brien, 1984; Anderson, 2008).

[18] In Appendix B.1, we perform several additional balancing checks, namely joint balancing checks whereby Cs137 is regressed on observable characteristics. These tests yield similar results.

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	0.025	0.003	−0.005
	(0.021)	(0.027)	(0.027)	(0.030)	(0.052)
Female	−0.001	−0.002	−0.001	−0.002	−0.005
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Employed in April 1986	0.001	0.002	0.004**	0.003	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Unemployed in April 1986	−0.000	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
If employed: Qualified or highly qualified	0.002	−0.000	−0.000	0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)
Children before 1986	−0.002**	−0.002	0.000	−0.000	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Older siblings	−0.000	0.001	0.000	0.001	0.005
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Smoke before 1986	0.001	0.001*	0.001	0.001	−0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Educational attainment in April 1986					
Lower secondary and secondary	0.001	0.002	0.002	0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Upper secondary	0.000	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Tertiary	−0.002	−0.004***	−0.005***	−0.004	−0.004
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
In school or college education	0.000	0.000	−0.000	0.000	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Highest parental education					
Lower secondary education	0.000	0.001	0.001	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Secondary education	0.005***	0.004**	0.001	0.002	0.004
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Upper secondary	−0.003***	−0.000	0.001	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Number of tests	−0.001	−0.003**	−0.002	−0.002	−0.006*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Observations	4440	4440	4440	4440	4440
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 sorting on observables, it might be possible that our results are driven by sorting on unobservable characteristics. The concern is 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. Our instrumental variable is based on two components that are arguably exogenous to residential sorting, namely local rainfall during a critical window of ten days in 1986, and the amount of available radioactive matter while the plume was above a place. In the following, we explain under what conditions each component separately and both components together can be considered exogenous.

IV component I: local rainfall during a critical time window. At the core of our instrumental variable strategy is local rainfall, which is one of the main determinants of ground radiation. If it rained a lot while the plume was above a place, this place ended up with a high level of ground radiation. If it rained little, the amount of ground radiation was smaller. However, local rainfall as an instrument can be problematic as it may itself be correlated with residential sorting. For example, if people with lower cognitive skills live at higher altitude, and places at higher altitude have more rainfall on average, the instrument would not be valid because it is likely correlated with differences between people living at higher and lower altitude.

To construct a valid instrument based on local rainfall, it is critical to isolate variation in rainfall that is idiosyncratic, i.e. that is unsystematic and, thus, independent of residential sorting. We argue that local rainfall in late April and early May 1986 is a valid instrument if we condition on the average level of rainfall in a given municipality at the same time of year. The average level of

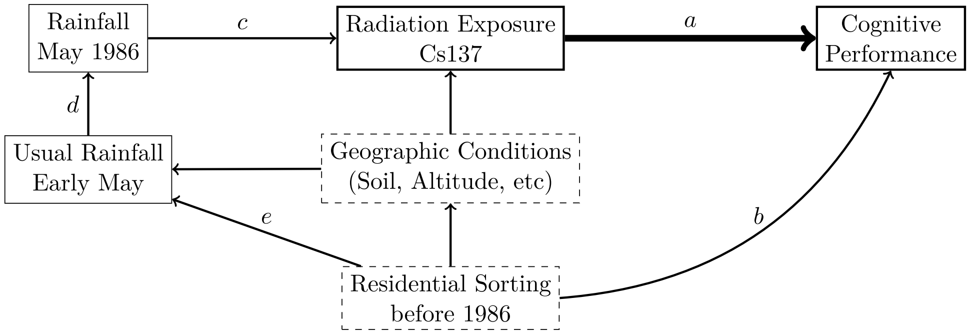


Fig. 3. Rainfall in late April/early May 1986 as an Instrument
Notes: This DAG illustrates some of the causal relationships between residential sorting, radiation exposure and cognitive performance. The relationship of interest is arrow a. The critical identification assumption is that rainfall in late April/early May 1986 is not directly affected by residential sorting or geographic conditions.

local rainfall is the amount of rainfall people can expect in a given place. If rainfall was to influence where people live, it should be the average amount of rainfall but not unsystematic deviations from the average. In other words, location decisions may well depend on how much it rains in a typical year or a typical season, but they should not depend on how much it rains this week as opposed to the same week last year or next year. When we control for the average level of rainfall in late April and early May, the remaining variation in rainfall in late April and early May 1986 measures the deviation from the average, and this variation can be considered orthogonal to residential sorting.

The DAG in Fig. 3 illustrates the rationale behind using idiosyncratic rainfall to construct the instrument. The causal effect of interest is arrow a. The confounder is residential sorting, which has a direct effect on cognitive performance (arrow b) as well as indirect effects through radiation. The direct effect stems from the fact that people with different abilities may choose to live in different places. We consider here two indirect effects. First, residential sorting affects the amount of rainfall a person is exposed to, which in turn affects their radiation exposure after the disaster. Second, residential sorting affects the geographic and weather conditions (besides rainfall) in a person's place of residence, which in turn affects radiation exposure. For example, some soil types are more prone to a higher level of ground radiation because radionuclides remain close to the surface whereas with other soil types they get absorbed into deeper layers (Arapis et al., 1997).

The critical assumption for instrument validity is the absence of an arrow from geographic conditions to rainfall in early May 1986. Whether it rains a lot on a particular day is not directly affected by geographic conditions. An example for this assumption is that altitude affects how much it typically rains in a place, but it does not affect whether it rains more today that it did yesterday or it will tomorrow. Using rainfall in late April/early May 1986 is a valid instrument once we control for average rainfall around the same time. This control eliminates the systematic relationship between residential sorting and the usual amount of rainfall (arrow e) as well as the correlation between the usual amount of rainfall and the rainfall on the critical days in April and May 1986 (arrow d).

The DAG also shows no direct effect of rainfall in early May 1986 on cognitive performance. If such a link existed, the exclusion restriction would be violated and the instrument would be invalid. We argue that the direct link (or a link via channels other than radiation) is implausible because we consider rainfall on 10 days 25 years before the outcome is measured. It is simply not plausible that rainfall on any ten days has a systematic effect on an outcome so many years later unless it coincides with a massive event such as Chernobyl. Given that there was no other event at the same time that would interact with rainfall and affect cognitive skills, we view the exclusion restriction as satisfied. In Appendix B.4, we also present a DAG with the local amount of radioactive matter in the plume.

IV component II: available radioactive matter in the plume. To increase power in the first stage of the instrument, we add a second component to the construction of the instrument, namely the amount of available radioactive matter in the plume. The radioactive plume entered Germany at its south-eastern tip around April 26, 1986 and left via the North Sea around May 8. On its journey, the amount of radioactive matter in the plume decreased as it was gradually rained down and deposited on the ground.[19]

The gradual decline in the amount of radioactive matter means that the same amount of rainfall leads to more ground deposition in the south-east than in the north-west of Germany. To account for this difference across space, we construct the instrument by interacting 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.[20]

$$z_m = \ln(rain_m^{86} \times matter_m). \tag{3}$$

[19] See Appendix for a graph illustrating the decline of the amount of radioactive matter along the trajectory of the plume.

[20] 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.

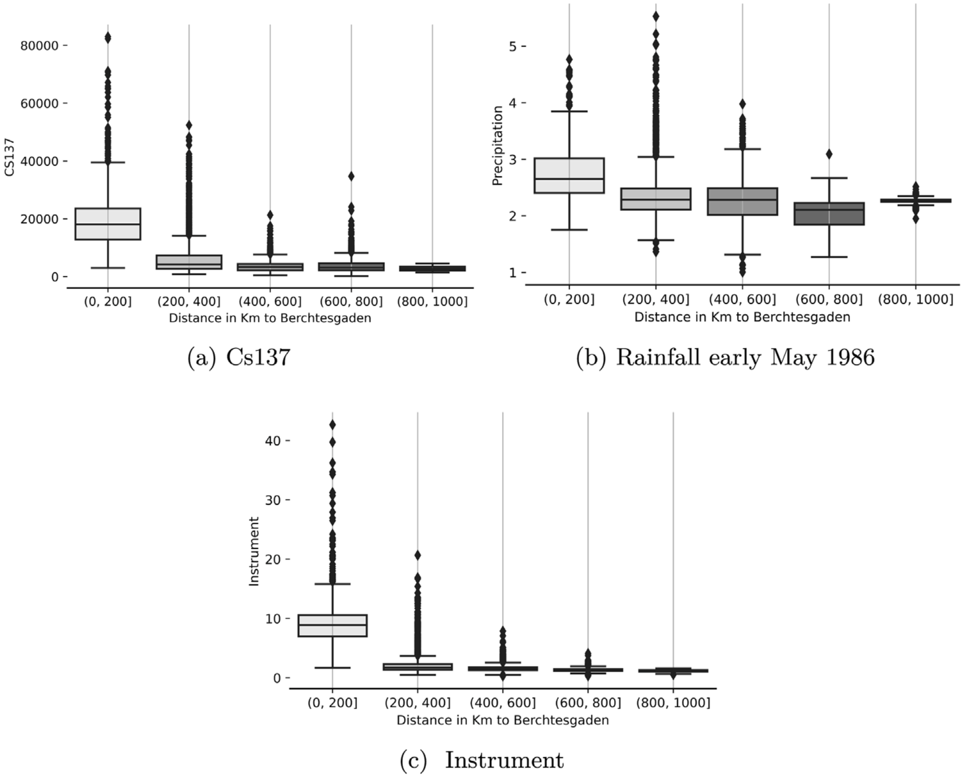


Fig. 4. Variation in Radiation, Rainfall and the Instrument
Notes: Panel (a) shows the variation in the level of ground radiation (Cs137 in $\mathrm{kBq/m^2}$) in May 1986 across German municipalities. The horizontal axis is split into five intervals representing the distance to Berchtesgaden, the south-western tip of Germany. Panel (b) shows the variation in rainfall between April 29 and May 9, 1986 across municipalities. Panel (c) shows the variation in the instrument $\ln(rain_m \times matter_m)$; $rain_m$ is the amount of rainfall in the aforementioned time window, $matter_m$ is the amount of available radioactive matter in the plume.

We use the log of this interaction because the first stage fits considerably better with logs than with levels. One reason for the better fit is that the amount of radioactive matter declines non-linearly as the plume moved towards the North-West (see Figure 8 in Appendix A.6.1). Another reason is that the relationship between rainfall and radiation appears non-linear: moving from a low to an intermediate level of rainfall leads to a greater increase in radiation compared to moving from an intermediate to a high level of rainfall.,[21]

The way we view the instrument is that rainfall is the main causal force that affects radiation exposure, whereas the available matter in the plume amplifies the first stage. Fig. 4 shows why the interaction between rainfall and the available amount of radioactive matter improves the first stage. Each panel shows the variation of a variable at different distances to Berchtesgaden, the entry point of the plume. The average ground deposition of Cs137 drops considerably between the first 200 km and beyond (Panel a). We do not see a similar drop in the amount of rainfall in early May 1986 (Panel b). Once we combine rainfall with the amount of radioactive matter in the plume – shown in Panel (c) – the instrument exhibits a similar drop across space as the local level of fallout in Panel (a).

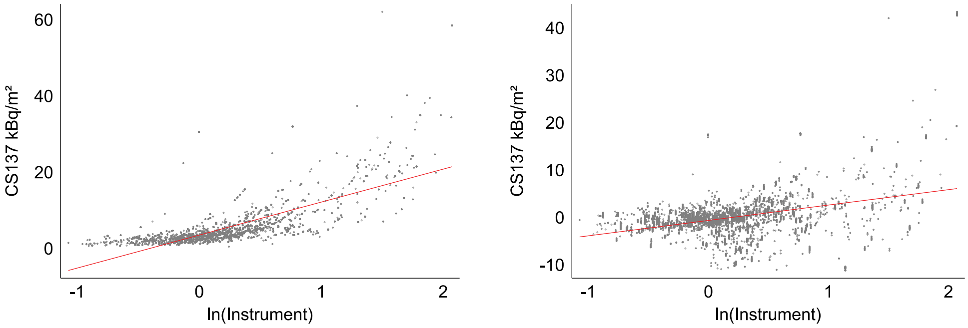
First stage and instrument relevance. In the first stage regression, we control for the same individual-, municipality- and county-level characteristics as in the OLS regression in Eq. (1),

$$\mathrm{Cs137}_{m(s)} = \lambda_0 + \lambda_1 z_m + \boldsymbol{X}'_{\boldsymbol{i(m)}}\boldsymbol{\kappa} + \rho_s + \eta_{ims}. \tag{4}$$

Fig. 5a 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. The regression line in Fig. 5b represents the first-stage coefficient λ_1 in Eq. (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.[22]

[21] In Appendix B.5, we show plots for the first stage with logs and levels.

[22] See Table 3 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.14 that the participation in the surveys is uncorrelated with personal characteristics.



(a) Raw correlation (b) Correlation with controls

Fig. 5. First-stage correlation $\ln(matter \times rainfall)$ *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 individual characteristics, altitude and 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. We have already established why rainfall in late April and early May 1986 can be considered a valid instrument in the estimation of the effect of radiation exposure on cognitive performance. However, given that the instrument is based on an interaction of rainfall with the available amount of radioactive matter in the plume, it is important to discuss the validity of both variables. Our main argument for instrument validity is that – conditional on appropriate controls – the amount of rainfall and the amount of radioactive matter should be independent of residential sorting (*conditional independence*). In our main specification, we control for average rainfall, which means that the remaining variation in rainfall can be considered idiosyncratic. Moreover, in robustness checks, we control for the distance to the entry point of the plume to break a correlation between residential sorting and the trajectory of the plume (Appendix B.6.3) and also control for the interaction between average rainfall and the amount of radioactive matter in the plume to ensure that the instrument is based on idiosyncratic rainfall only. We also run a robustness check whereby we only use rainfall as an instrumental variable.

In our view, the less controversial assumption is the exclusion restriction. It is difficult to think of a mechanism other than radiation through which either component of the instrument would affect cognitive test scores. Our instrument is based on idiosyncratic – that is, unsystematic – rainfall patterns on 10 days in late spring 1986. A violation of the exclusion restriction would mean that the rainfall on these days conditional on the typical level of rainfall has an effect on test scores in 2010 through a channel different from radiation. This would only be the case if a different shock happened during the same time that is unrelated to radiation but propagated through rainfall. We are not aware of any such shock occurring during these days.

5. Radiation and cognitive skills: Results

5.1. The effect of initial exposure on cognitive performance

Table 3 presents our baseline regression results. In Panel A, each coefficient is the result of an OLS regression of the test scores listed at the top on the level of Cs137 in a respondent's municipality of residence in May 1986. All regressions include fixed effects for the state of residence in 1986 as well as the individual and geographic controls described in Section 4.1. The outcomes are standardized to mean zero and standard deviation one, such that a coefficient of $\hat{\beta} = -0.01$ 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 an increase in Cs137 by one standard deviation ($sd = 5.87$). Further below, in Section 5.4, we provide additional guidance on the effect sizes by comparing the treatment with other types of radiation exposure.

The coefficients are negative throughout, and for four out of eight cognitive skills tests the effects are large and statistically significant at the 10%-level or below. The effect sizes range between zero for logical reasoning (Column 6) and 8.2% of a standard deviation for reading comprehension (Column 7). Perhaps the most meaningful 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.

To understand the magnitude of the effect, it is useful to compare the cognitive skill index with an IQ score. IQ scores are normalized to mean 100 and standard deviation 15. In this metric, an increase by 4.7% of a standard deviation is roughly equivalent to an increase in IQ scores by 0.7 IQ points.[23] Moreover, to provide a sense of magnitude for a one-standard deviation increase in initial ground radiation, we perform the following back-of-the-envelope calculation. The standard deviation of ground deposition is 5.87 kBq/m^2, which is about 1.1 times the mean ground deposition. If we apply this factor to the estimated average effective dose

[23] We choose this comparison because many readers are familiar with IQ scores. One should note, however, that the cognitive skill index has some overlap with, but is not fully equivalent to, an IQ test.

Table 3
The effect of radiation on cognitive performance — OLS and IV results.

	Math	Reading	List. comp.	ICT	Scient. lit.	Reas.	Read. speed	Percp. speed	Cog index
A. OLS Estimates									
OLS coefficient	−0.011***	−0.013**	−0.008*	−0.005	−0.004	−0.000	−0.007*	−0.004	−0.008**
	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
B. IV Estimates									
2SLS coefficient	−0.015**	−0.021**	−0.013	−0.009	−0.006	−0.008	−0.007	−0.005	−0.012**
	(0.007)	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)	(0.006)
First Stage	6.841***	6.426***	6.156***	6.792***	6.830***	6.159***	6.592***	6.158***	6.463***
	(0.958)	(1.064)	(0.930)	(1.249)	(1.257)	(0.933)	(1.010)	(0.933)	(1.029)
Reduced form	−0.105**	−0.138**	−0.080	−0.060	−0.044	−0.047	−0.046	−0.033	−0.081**
	(0.050)	(0.054)	(0.052)	(0.039)	(0.043)	(0.051)	(0.052)	(0.056)	(0.040)
F-statistic	51.0	36.5	43.8	29.6	29.5	43.6	42.6	43.6	39.5
Observations	2652	2666	3172	3312	3286	3169	3611	3170	4440

Notes: This table displays the OLS and 2SLS estimates of the impact of Cs137 on cognitive test scores. All specifications include state fixed effects as well as the controls listed in Section 4.1 in the paper. The instrumental variable is $ln(rain_m^8 6 \times matter_m)$. The first stage is the regression of $Cs137_m$ on the instrument and all controls and fixed effects. The reduced form is the regression of the respective cognitive test score on the instrument and all controls and fixed effects. The F-statistics vary across columns because each test was taken by a different random subsample of respondents. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***$: $p < 0.01$, $**$: $p < 0.05$, $*$: $p < 0.1$.

from the Chernobyl radiation (0.6 mSv), we get a value of 0.66 mSv. This value is equivalent to 66 panoramic dental X-rays, 6 chest X-rays or 1.65 mammograms. As such, the results show that low doses of radiation similar to those received in standard medical procedures can lead to cognitive impairments over a time horizon of over 20 years.[24]

Panel B presents the instrumental variable estimates from regressions with all controls and state fixed effects. Across outcomes the first stage coefficients are positive, which means that the instrument works as intended: a higher level of rainfall during the critical period of 10 days after the disaster and a higher amount of radioactive matter in the plume leads to higher ground radiation. The F-statistics indicate that the instrument is sufficiently strong, with test statistics between 32 and 66. The first stage coefficients and F-statistics differ across columns because each test is based on a slightly different random subsample.

Overall, the IV results confirm the OLS results. All coefficients are negative and the test scores for maths and reading comprehension are statistically significant at the 5%-level. The overall effect on the cognitive skill index, shown in Column (9), is negative and statistically significant. The coefficient is slightly larger than the OLS coefficient in Panel A but the order of magnitude is similar. Differences between OLS and IV estimates are not uncommon given that both estimators rely on different types of variation and attach different regression weights to observations. In terms of magnitude, the coefficient in Column (9) means that a one-standard-deviation increase in the initial radiation exposure leads to a reduction in test scores by $0.012 \times 5.87\% = 7\%$ of a standard deviation. Scaled to an IQ score, this effect is equivalent to a reduction by one IQ point.

In Appendix B.2, 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. *The effect of average exposure,1986–2010*

The results in Table 3 represent intention-to-treat (ITT) estimates. Depending on their place of residence in 1986, people were "treated" with different initial levels of ground radiation, which in turn affects cognitive test scores through biological and behavioral channels. The interpretation of the ITT coefficients comes with at least two challenges. First, the exposure to ground radiation is a long-term process rather than a one-off shock. People who continuously lived in a municipality with a high level of radiation in 1986 were exposed to a higher level of radiation over the next 25 years. A second challenge is internal migration. Even if moves are unrelated to the level of radiation, some people reduce their exposure by moving to an area with less radiation while others increase their exposure by moving in the opposite direction.

To address both challenges, we consider a person's average exposure between 1986 and 2010 as an alternative regressor. For each respondent, we compute the average exposure based on their places of residence between May 1986 and December 2010.[25] In the estimation sample, this variable has a mean of 3.89 kBq/m^2 and a standard deviation of 4.41 kBq/m^2. The mean and standard deviation of average exposure are lower than the mean and standard deviation of the initial exposure because of the decay of Cs137, which means that the exposure decreases over time and places with high and low initial radiation levels become more similar.

Table 4 displays the OLS and IV estimates. In the OLS estimates in Panel A, we find negative effects throughout, although only the effects on maths and reading speed are statistically significant. The coefficient of the cognitive skill index is −0.01, which means that

24 This calculation, admittedly, is somewhat crude. Measures of the ground deposition are usually provided in kBq per square meter, which measures the amount of ionizing radiation emitted per square meter. The relevant measure for medical procedures is the effective dose of radiation for the average person, i.e. the amount of radiation absorbed by human tissue. For the Chernobyl accident the BfS (2016) provides rough estimates of the effective dose of radiation for the average person. However, the link between ionizing radiation and effective dose is not immediate, as the effective dose largely depends on a person's lifestyle .

25 Comprehensive measures of Cs137 are only available for 1986. To compute the level of Cs137 in later years, we use the decay formula for Cs137.

Table 4
Effect of average exposure on cognitive test scores.

	Math	Reading	List. comp.	ICT	Scient. lit.	Reas.	Read. speed	Percp. speed	Cog index
A. OLS Estimates									
OLS coefficient	−0.013**	−0.012	−0.011	−0.004	−0.001	0.000	−0.020***	−0.006	−0.010*
	(0.006)	(0.008)	(0.007)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)	(0.005)
B.IV Estimates									
2SLS coefficient	−0.035**	−0.051**	−0.030	−0.020	−0.015	−0.018	−0.016	−0.013	−0.029**
	(0.017)	(0.021)	(0.020)	(0.014)	(0.015)	(0.019)	(0.018)	(0.021)	(0.015)
First Stage	3.011***	2.707***	2.652***	2.985***	3.001***	2.656***	2.845***	2.655***	2.793***
	(0.462)	(0.430)	(0.391)	(0.532)	(0.536)	(0.392)	(0.427)	(0.392)	(0.447)
Reduced form	−0.105**	−0.138**	−0.080	−0.060	−0.044	−0.047	−0.046	−0.033	−0.081**
	(0.050)	(0.054)	(0.052)	(0.039)	(0.043)	(0.051)	(0.052)	(0.056)	(0.040)
F-statistic	42.5	39.6	46.1	31.5	31.3	45.9	44.5	45.9	39.0
Observations	2652	2666	3172	3312	3286	3169	3611	3170	4440

Notes: This table displays the OLS and 2SLS estimates of the impact of the average exposure to Cs137 between 1986 and 2010 on cognitive test scores. The average exposure has been computed based on the level of Cs137 in a person's municipality of residents, taking into account moves to different municipalities. All specifications include state fixed effects as well as the controls listed in Section 4.1 in the paper.The instrumental variable is $ln(rain_m^8 6 \times matter_m)$. The first stage is the regression of $Cs137_m$ on the instrument and all controls and fixed effects. The reduced form is the regression of the respective cognitive test score on the instrument and all controls and fixed effects. The F-statistics vary across columns because each test was taken by a different random subsample of respondents. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: $***$: $p < 0.01$, $**$: $p < 0.05$, $*$: $p < 0.1$.

an increase in the average exposure between 1986 and 2010 by 1 $\mathrm{kBq/m^2}$ reduces the cognitive test score by 1 percent of a standard deviation. Scaled to the standard deviation in average exposure, $sd = 4.41$, this means that an increase in average exposure by one standard deviation reduces cognitive test scores by around 4.4% of a standard deviation. This result is very similar to the effect of initial exposure shown in Table 3. The IV estimates in Panel B are considerably larger than the OLS estimates. The coefficient of the cognitive skill index is -0.029, which means that an increase in the average exposure by one standard deviation reduces the cognitive skill index by 12.7% of a standard deviation. Potential reasons behind the difference between OLS and IV coefficients are measurement error and compliance. By constructing the average exposure over 25 years, we inevitably introduce measurement error because of the discrepancy between potential and actual exposure. To the extent that the measurement error is classical, it leads to attenuation bias in the OLS coefficient. The IV estimator also places greater weight on respondents who are more "compliant". Although it is difficult to exactly pinpoint compliers in our context, one source of imperfect compliance is internal migration. The instrument predicts the radiation level based on rainfall in the place of residence in 1986. This means that the first stage is likely stronger for people who never moved than for people who eventually moved.

5.3. Internal migration as a potential channel

An important potential causal channel is internal migration. If people move in response to exposure, this may explain the negative results of radiation on cognitive performance. Although migration responses would not invalidate our identification strategy, it would change the interpretation of the estimates. Rather than radiation affecting cognitive performance mainly through physiological effects, part of the explanation might be that people with higher cognitive skills move to less contaminated areas. After performing several robustness and balancing checks, we can rule out that migration is an important explanation for the observed effects.

Table 5 shows that many respondents moved from their original municipality of residence between 1986 and 2010. Until January 1, 1988, 12.2% moved, whereas until 2010, close to 60% moved. When we look at movers out of state, this figure is lower but still considerable: by January 1, 1988, 7.3% have moved to a different state. By 2010, over one third of respondents had moved to a state that was different from their state of residence in 1986. In Appendix B.3.1, we also show that movers and non-movers differ in their observable characteristics: for example, movers are younger and better educated than non-movers. However, the selectivity of moves on its own is not sufficient to explain the reduced form coefficient β. It would only explain it if the likelihood to move was systematically related to the initial level of Cs137.

In Columns (1) and (2) of Table 5, 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. In Columns (3) and (4), we perform the same analysis with an indicator that equals unity if a person has moved to a different state up until a given year. Overall the results do not indicate that radiation had an impact on internal migration. Given the level of radiation and given the information that was available at the time, the lack of a response is fairly unsurprising. In large parts of the country the additional Chernobyl-induced radiation was considered low and, thus, it is unlikely that radiation would influence a decision as profound as moving. In addition, people only learned about the regional level of Cs137 several years after the disaster, by when the radiation exposure was considerably lower than in 1986. In Appendix B.3.1, we also test whether the migration response to Chernobyl-induced radiation differed between high- vs. low-educated and old vs. young respondents but find no evidence of a differential response.

Table 5
No evidence of a migration response.

	Share of movers since 1 May 1986	Movers		Share of state movers since 1 May 1986	State movers	
		(1)	(2)		(3)	(4)
Until 1988	12.2%	0.000	0.000	7.3%	0.000	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Until 1990	23.5%	0.000	0.000	13.3%	−0.000	0.001
		(0.001)	(0.002)		(0.001)	(0.002)
Until 1995	39.4%	−0.001	−0.003	22.4%	−0.002*	−0.001
		(0.001)	(0.002)		(0.001)	(0.002)
Until 2010	59.5%	0.001	0.001	35.7%	−0.001	0.002
		(0.001)	(0.002)		(0.001)	(0.001)
Controls:						
State FE		No	Yes		No	Yes
Controls		No	Yes		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. In Columns (3) and (4), the outcome is an indicator that equals one if a person moved out of their state of residence of May 1986 up to a year given on the left. Standard errors, clustered at the county level, are displayed in parentheses. Significance levels: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

5.4. *Effect magnitude and discussion*

The estimates presented in Table 3 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% of a standard deviation. If we use the scale of IQ tests (mean 100, standard deviation 15) this effect is equivalent to 0.7–1.1 IQ points. With one 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.[26]

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 0.6 mSv (BfS, 2016), which is one-third of the effective yearly dose of background radiation (2mSv), or the equivalent of 6 chest X-rays or 1.5 mammograms. People in areas with higher contamination, for example Munich, received an effective dose of 2mSv, which is around the same as the dose from 20 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.4, 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 decrease in math scores by almost 100% and a decrease 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.[27]

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.[28] 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. *Robustness checks*

In the appendix, we perform a series of robustness checks. To address concerns about the data linkage procedure, we show in Appendix B.7 that our estimates are robust to alternative linkage procedures. In Appendix B.9, we also perform a robustness check

[26] 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.

[27] The effect sizes in Almond et al. (2009) refer to the effects of $log(CS137)$ at the municipality-level reported in Table 4. The effect on math scores is −4.491, which is 96% of $sd(math) = 4.66$, reported in Table 1X. 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.'

[28] Source: vital statistics provided by Destatis.

whereby we only include municipalities that had a measuring station for Cs137 in 1986. This test alleviates the concern that the results are biased by measurements of Cs137 that are entirely interpolated from other municipalities. A further concern is that our results are driven by differential mortality. The analysis in Appendix B.14 suggests that this concern is unwarranted.

We also perform a series of tests addressing potential biases in the estimation. One concern is that the state fixed effects – along with controls for municipal and individual characteristics – are not enough to eliminate the confounding influence of residential sorting. One potential solution would be to include county fixed effects and exploit variation within counties across municipalities. However, given that only 198 municipalities are included in the estimation sample, there are very few counties with more than one municipality in the sample. As an alternative, we perform an analysis with grid cell fixed effects. We divide the map of Germany into a grid of 120-by-120 km cells, and include fixed effects for the grid cells. In this exercise, we compare respondents who live in the same grid cell but are exposed to different levels of radiation. In order to avoid that the results are driven by the locus of the grid, we perform the same analysis 500 times, each time shifting the grid by 1 km in the north-south and east–west direction. The results, discussed in Appendix B.10, show that our results are robust to the inclusion of more fine-grained fixed effects.

In a series of robustness checks in Appendix B.9, we alleviate concerns that the results are driven by outliers. The results are robust to dropping the top one percent of observations with the highest exposure to Cs137, as well as to dropping municipalities with five or fewer observations in the estimation sample.

One concern with the analysis is that we compare the outcomes of respondents from different age groups, across which there might be systematic differences in cognitive performance. In Appendix B.6.4, we show that our results are robust to flexible controls for age.

In Appendix B.6.1, we present a large number of OLS estimates whereby we control for additional potential confounders. The results prove robust to controls for the level of radon in a respondent's municipality of residence in 1986, information on a person's migration status, additional family characteristics, additional municipality characteristics, weather conditions on the interview date, and the inclusion of fixed effects for a respondent's state of residence in 2010. We show that the results are robust to the inclusion of any one of these sets of controls as well as various combinations of control variables.

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, which we interact with the amount of radioactive matter in the plume. 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.24 show no significant relationship in the years after Chernobyl.

In Appendix B.11, we provide estimates based on a sample of non-movers. These results help us to gauge how important subsequent migration is in explaining the ITT effect. In line with the results from Table 5 – showing that internal moves are unrelated to radiation – we find that the effects are similar in a subsample of non-movers and the full sample.

Finally, In Appendix B.12, 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.19 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.

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 between 4.4% and 7% of a standard deviation. This is a reasonably large effect given that the effective radiation dose from a one-standard-deviation higher initial exposure is roughly equivalent to the dose from standard medical procedures. For example, this dose is equivalent to the dose of six chest X-rays or 1.65 mammograms.

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 1,000 km away from the German border, the disaster's negative consequences significantly affect the German population. Given the proliferation of nuclear power worldwide, such disasters may occur again in the near future, especially because nuclear power plants can be targets in wars and conflicts.

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 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. The additional effective radiation dose received by the average person is of a similar magnitude to the dose received from medical procedures. Our results show that such radiation doses can have negative long-term effects on cognitive performance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2023.102785.

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