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Inventing Green: Environmental Shocks and the Long-Term Reorientation of Innovation

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Abstract

How are preferences for innovation formed, and what determines the long-run direction of technological change? This paper shows that early-life exposure to environmental accidents can durably reorient inventive effort decades later, even in the absence of targeted policy. I study radioactive fallout from the 1986 Chernobyl nuclear accident across Sweden, exploiting plausibly exogenous variation in local exposure driven by rainfall. Combining municipality-level fallout data with Swedish patent records from 1967 to 2021, I find that more exposed areas experienced a persistent increase in green patenting, with no change in total patenting. The effect emerges only in the early 2000s, and is driven by individuals exposed during childhood: matching inventor-level data with detailed administrative records, I show that individuals exposed to fallout during their formative years are more likely to enter the patent system as green inventors and to begin their inventive careers with green technologies, consistent with a cohort-based entry mechanism. A simple model of directed technical change with formative exposure rationalizes these findings. In addition, the paper shows that green patents originating from more exposed areas do not have a lower number of citations than other patents, suggesting that the results are not driven by low-quality innovations.

JEL classification codes: D91; O31; Q53; Q55

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I. Introduction

A large literature in economics studies how prices, policies, and institutions shape the rate and direction of technological change (Romer 1990; Aghion and Howitt 1992; Acemoglu 2002). However, much less is known about how innovators' underlying preferences are formed in the first place, and whether experiences early in life can durably redirect inventive effort decades later. This question matters because the transition to new technologies, such as low-carbon innovation, often requires not only stronger incentives for existing inventors, but also the entry of new cohorts whose interests and orientations differ from those of incumbents.

Existing research tends to focus on market-based drivers of directed technical change. Higher energy prices, environmental regulation, and carbon taxes have been shown to induce cleaner innovation, largely by encouraging inventors already active in green technologies to intensify their efforts (Popp 2002; Calel and Dechezleprêtre 2016). At the same time, a growing literature documents strong path dependence in innovation, suggesting that once inventors specialize, changing the direction of their research is difficult (Acemoglu, Akcigit, et al. 2016; Aghion, Dechezleprêtre, et al. 2016). Together, these findings raise a puzzle: if incentives primarily operate on existing inventors, where do new pathways of innovation come from?

This paper proposes a complementary mechanism through which the direction of technological change can evolve: early-life exposure to environmental risk can shape the technological orientation of individuals who later become inventors. Under this mechanism, new technologies arise not because existing inventors change their research interests, but because new cohorts of inventors enter with different preferences and interests. As a result, the effects of exposure may be delayed, becoming visible only when affected cohorts reach adulthood.

To test this hypothesis, I use variation in radioactive fallout from the 1986 Chernobyl accident that spread to Sweden, a country that was geographically distant from the disaster but received considerable levels of fallout. The identification strategy exploits an important feature of the fallout distribution, namely that virtually all of the Chernobyl releases were spread through rainfall. This produces plausibly exogenous variation in fallout levels across Swedish municipalities. Importantly, exposure occurred long before climate change became a central concern for policymakers, allowing us to isolate formative experiences from contemporaneous incentives.

I then combine municipality-level fallout exposure with Swedish patent records from 1967 to 2021, distinguishing green from non-green patents using the Cooperative Patent Classification (CPC) Y02 scheme for climate change mitigation technologies. Using a difference-in-differences specification that interacts 1986 fallout levels with time-period dummies, I find that municipalities more exposed to fallout experienced a significant increase in green innovation. There is no corresponding increase in overall patenting, indicating that the effect reflects a reallocation of inventive activity rather than a general rise in innovation. Notably, the increase in green patenting emerges only in the early 2000s—nearly two decades after the accident. In the post-2000 period, a one standard deviation increase in 1986 fallout exposure is associated with an increase in green patents per capita of approximately 0.15 standard deviations. This corresponds to an increase of about 12% relative to the municipality-average of green patents per capita. Using citation data on post-2000 patents, I show that the shift toward green innovation is not driven by low-impact or symbolic patenting.

Since total patenting is unchanged, the welfare gain stems from reallocating inventive effort toward green technologies. Green patents generate higher social returns than non-green ones, due to positive environmental externalities (Acemoglu, Aghion, et al. 2012) and knowledge spillovers (Dechezleprêtre et al. 2014). A conservative back-of-the-envelope calculation, using literature benchmarks on patent values and the observed 12% per-capita increase in green innovation in exposed areas, suggests cumulative social benefits on the order of \$17–\$165 million in Sweden, with a midpoint estimate of roughly \$63 million.

Given that the time lag from idea to patent application is normally estimated to be only a few years, the delayed effect on green patents is unlikely to have occurred as a contemporaneous response to the Chernobyl fallout. The timing of the effect suggests two competing explanations. The first one is a cohort-based behavioral mechanism, whereby early-life exposure to an environmental accident impacts the long-run technological orientation of individuals who later became inventors. In turn, this generates a delayed effect on patents that emerges only when exposed cohorts are old enough to innovate.

The other is a discourse-based explanation, under which the observed increase in green patenting reflects a broader rise in environmental concern. In the early 2000s, there was an increase in media coverage of climate change issues, coinciding with Al Gore's 2006 film *An Inconvenient Truth* and the 2007 Intergovernmental Panel on Climate Change (IPCC) report, which highlighted the rising scientific consensus about the role of human activity in causing climate change and warned that conditions were likely to worsen substantially in the future. If this channel is correct, the observed increase in green patenting would be driven by the contemporaneous rise in climate change salience, with inventors in fallout-affected areas responding more strongly to global environmental discourse during the early 2000s, rather than by a cohort-based effect rooted in early-life exposure.

To evaluate first the cohort-based mechanism, I turn to individual-level inventor data by linking patent records for a subset of the innovations to administrative registers that identify inventors' age and municipality of residence in 1986. This procedure yields two main findings. First, the early-2000s increase in green patenting in fallout-affected areas is driven by individuals who were below age 20 at the time of the disaster and were exposed to fallout when young. Second, individuals exposed to fallout during childhood are significantly more likely to have a first patent that is green. Taken together, these findings provide support of a persistent cohort effect operating through entry into green innovation. Then, I formalize this mechanism in a simple model of directed technical change in which early-life exposure to environmental risk shifts cohort-specific preferences over technologies, so that innovation is reoriented toward green technologies through entry of new inventors rather than reallocation by incumbents.

To assess the alternative discourse-based explanation, I combine survey evidence with newspaper data. Using a large, nationally representative survey conducted annually since 1986, I first show that there is no general increase in pro-environmental concern in more exposed municipalities over time, which speaks against an explanation based on a broad rise in climate awareness. Consistent with this, an analysis of the universe of digitized Swedish newspapers reveals that while references to "Chernobyl" and "cesium" remain more prevalent in local newspapers in affected areas in the early 2000s, there is no corresponding increase in mentions of "climate change." At the same time, the survey data indicate that individuals who were exposed during childhood hold more favorable views toward green innovation later in life. This pattern supports the cohort-based mechanism, whereby early-life exposure shapes long-run technological orientation, rather than a contemporaneous shift in climate-related attitudes.

Finally, using a combination of municipality-level and individual-level administrative data, including administrative records on educational attainment for the universe of the Swedish population, I rule out a range of alternative channels, including human capital formation and government transfers in fallout-affected areas. Taken together, the evidence supports a cohort-based mechanism in which early-life exposure influences who enters green innovation, rather than due to changes in local economic conditions, incentives, or human capital accumulation.

This paper contributes to several strands of the literature. First, it relates to a broad economics literature on green innovation and the drivers of environmentally directed technological change, in particular how individual inventors respond to environmental policies and incentives. One strand emphasizes the role of institutional policy frameworks, such as cap-and-trade systems and emissions trading schemes, in encouraging low-carbon innovation (Gans 2012; Calel and Dechezleprêtre 2016; Calel 2020; Yao et al. 2021; Cantone et al. 2023). Another line of work examines how energy prices influence inventive activity. Early studies show that higher energy prices induce innovation in cleaner technologies (Newell et al. 1999; Popp 2002), while more recent research complementing this by finding that most of the innovation response comes from inventors already active in clean technologies, with limited responsiveness among new entrants (Dugoua and Gerarden 2025). The latter finding is consistent with the role of path dependence and the difficulty of shifting the research direction of inventors once their specialization is established (Acemoglu, Aghion, et al. 2012; Acemoglu, Akcigit, et al. 2016; Aghion, Dechezleprêtre, et al. 2016). Unlike much of the existing literature, which focuses on how inventors respond to external incentives such as prices or policies, this paper identifies a non-market, formative channel through which environmental shocks can influence the direction of technological change. The findings suggest that even in the absence of targeted interventions, individuals who experienced environmental accidents in childhood are more likely to become green innovators later. In turn, as older generations are replaced by younger cohorts, this process contributes to a longer-run reallocation of aggregate inventive activity.

Second, the paper contributes to research on the supply of inventors and the determinants of who becomes an innovator. Recent work highlights the roles of gender, family background, cognitive ability, and social networks in shaping inventive potential (Aghion, Akcigit, et al. 2017; Bell et al. 2019; Kim and Moser 2025). Still, less is known about how formative environmental experiences influence not just entry into innovation, but the direction of inventive effort. This paper shows that early-life exposure to Chernobyl fallout led to a persistent increase in green innovation among affected cohorts, pointing to a novel behavioral channel through which non-market shocks shape the composition and orientation of the inventor pool. These findings relate to a broader social science literature on the lasting influence of early-life experiences. A large body of work suggests that shocks during childhood or young adulthood can have durable effects on beliefs and behavior in adulthood. This has been documented in economics, but also in political science and other fields (Sears and Funk 1999; Alesina and Fuchs-Schündeln 2007; Malmendier, Tate, et al. 2011; Dinas 2013; Malmendier and Nagel 2016; Daniele et al. 2023; Graeber et al. 2024; Bietenbeck et al. 2025; Jiang et al. 2025). The perhaps closest paper here—also relating to an environmental shock—is probably Severen and Benthem (2022), who show that those who came of driving age during the oil crises of the 1970s drive less several decades later. This paper adds to this literature by showing that environmental shocks in childhood can influence the technologies individuals go on to develop decades later, not just economic behaviors, even in the absence of targeted incentives.

Finally, the paper builds on a broad literature studying the long-run effects of environmental catastrophes. One strand of this literature examines the relationship between natural disasters and environmental accidents on innovation using panels of many different events, typically exploiting cross-country or regional variation in exposure over time (Miao and Popp 2014; X.-X. Zhao et al. 2022; L. Zhao and Parhizgari 2024). Another strand studies the impact of extreme whether on technology adaption (Baylis and Boomhower 2026). While these studies provide evidence that environmental shocks can influence innovative activity and technological adaption, a drawback of these studies is that they rely on heterogeneous events and institutional contexts, making it difficult to isolate the underlying mechanisms. A second strand studies the long-term consequences of single, well-defined environmental accidents and natural disasters using natural-experiment designs.

Examples include work on the 1930s Dust Bowl (Hornbeck 2012), Hurricane Katrina in 2008 (Groen and Polivka 2008; Gallagher and Hartley 2017; Deryugina and Molitor 2020), and, as in this paper, the Chernobyl accident (Almond et al. 2009; Lehmann and Wadsworth 2011; A. Danzer and N. Danzer 2016; Mehic 2023). While these papers provide a more straightforward identification, they focus on the effects on human capital and health, which are different questions than the ones posed in this paper. This paper bridges these two literatures by exploiting a single, plausibly exogenous environmental shock with clean identification, while directly studying its long-run effects on green innovation and inventor entry. In doing so, I show that environmental accidents can durably reorient technological change not through incentives, but through cohort-specific entry into innovation decades later.

The rest of the paper is structured as follows. Section II provides a background to the Chernobyl disaster, while Section III describes the data. Section IV presents the empirical strategy and the main results. Section V provides evidence in favor of the cohort-based channel. Section VI provides corroborating evidence from survey data, and discusses alternative channels. The paper concludes with Section VII.

II. Background

On April 26, 1986, an explosion in reactor 4 of the Chernobyl nuclear power plant released large amounts of radioactive material into the atmosphere. The resulting fire burned for ten days, sending a radioactive plume across much of Europe. While the first cloud reached Sweden on April 27, the most significant fallout occurred with heavy rainfall during the night of April 28–29, leading to substantial ground contamination in parts of the country. Nuclear accidents release a range of radioactive isotopes, but the most stable and environmentally persistent is cesium-137, which has a half-life of approximately 30 years. Sweden received about 5% of the total cesium fallout released by the disaster (Moberg 1991). Due to its chemical properties, cesium-137 binds to soil and accumulates in plants and animals, making it easily traceable over long periods.

To mitigate public health risks, Swedish authorities implemented consumption restrictions in heavily affected regions. These primarily took the form of threshold limits on meat, berries, fish, and mushrooms, disproportionately affecting rural populations whose livelihoods depended on local resources. Thousands of reindeer and other wild animals were destroyed due to contamination, causing further disruption to rural economies. Although the most severe health effects were concentrated in the Soviet Union, Swedish studies have documented a positive association between fallout exposure and increased cancer incidence (Tondel et al. 2006; Alinaghizadeh et al. 2016). Specifically, authorities estimates that approximately 300 excess cancer deaths will occur in Sweden over a 50-year horizon as a result of Chernobyl-related exposure (Hult 2011).

Importantly, fallout deposition varied substantially across regions. In the most affected areas, ground deposition was close to that outside the Chernobyl exclusion zone, whereas other parts of Sweden were essentially spared (Holmberg et al. 1988). This localized variation in exposure, largely driven by variation in rainfall, provides a natural experiment that enables us to study the long-run effects of environmental disasters on innovation behavior.

III. Data

The paper utilizes four types of data: municipality-level data on radiation and patents, individual-level register data on inventors and on the full population, survey data, and, finally, newspaper data. These data are briefly described below. Table A.1 of Online Appendix A reports the summary statistics, while Online Appendix B provides additional details on the data sources.

III.A. Municipality-Level Data

1. *Radiation Data*

Immediately after the accident, authorities conducted aerial measurements of ground deposition of cesium. These measurements commenced May 9 and continued through June 3, producing a detailed map of ground-level cesium deposition categorized into exposure zones. Using this map, I employ ArcGIS to compute the average cesium deposition for each municipality. In all, there were 284 municipalities in Sweden at the time of the Chernobyl disaster, and the resulting municipality-level variation in fallout is illustrated in Figure 1. The northernmost and southernmost parts of Sweden experienced almost no fallout. Instead, the highest concentration of ground cesium deposition was in coastal areas in the central parts of the country. Ground contamination is generally expressed in kilobequerels per square meter (kBq/m^2), however, in the empirical analysis, I standardize the fallout variable so that the mean is zero and the standard deviation is equal to unity. Approximately 17% of the Swedish population lived in above-average fallout areas, and in these areas, there was an average exposure of 1.50 standard deviations.

2. *Patent Data*

The patent data, except for the data on citations, comes from the Swedish Intellectual Property Office, which is the government agency handling patent applications. The dataset comprises nearly all patent applications in Sweden from 1967 to 2021. Coverage is complete from 1971 onward, with some missing records for 1967–1971; this period is included primarily to assess pre-trends and should be interpreted with appropriate caution. To classify a patent as a green patent, I use the CPC Y02 system, which tags a patent as "green" if it relates to technologies that control, reduce, or prevent greenhouse gas emissions. The Y02 class is the most common system used to classify patents as relating to climate change mitigation, and is widely used in innovation research to differentiate between green and non-green patents (Calel 2020; Cantone et al. 2023). Prior to the introduction of the Y02 system, climate mitigation technologies were scattered across multiple classifications, making it difficult to identify and access them in a structured way. The Y02 tag was introduced in 2010, meaning that earlier patents are retroactively reclassified. Patent classification, whether for a new patent or a reclassification of a pre-2010 patent, is carried out by the patent office without consulting the inventor. Patents may carry multiple classification codes, and it is uncommon for a patent to be classified exclusively under Y02. Accordingly, a patent is classified as green if it carries the Y02 tag, regardless of other classifications.

In total, there are 1,072,016 patents in the dataset, of which 25,185 have the Y02 tag, which corresponds to 2.3%. Figure 2 plots the total number of patents and the share of patents classified with the Y02 tag. The share of green patents declined slightly in the late-1970s and early-1980s, remaining stable at around 2%, until increasing to around 3% starting in the early 2000s. The data on citations is from the European Patent Office's PATSTAT database, and covers the period from 2000 to 2016.

III.B. Register Data

1. *Inventor Data*

To investigate the individual-level mechanisms behind the shift toward green innovation, I continue by linking a subset of the patents to register data on the inventors listed on each patent. For each inventor, I obtain information on their birth year and municipality of residence in 1986, which makes it possible to identify individuals who were children at the time of the Chernobyl accident, and to match the fallout level in their municipality of residence in 1986 with whether their filed patent was green or not. I also use information on whether the individual's first registered patent was green.

2. *Individual-Level Register Data*

To evaluate potential labor market responses to environmental exposure, and to evaluate potential mechanisms, I use the *LISA* database, maintained by the Swedish Statistics Agency.[1] The LISA database consists of annual observations for the entire Swedish population from 1990 to 2021, and includes detailed annual information on individual income, employment status, educational attainment, study grants, and demographic characteristics for all individuals residing in Sweden. For employed individuals, the data also

[1]Shorthand for *Longitudinell integrationsdatabas för sjukförsäkrings- och arbetsmarknadsstudier* ("longitudinal integrated database for health insurance and labor market studies").

contain information on the individual's sector of employment, which allows for a granular breakdown. The data are structured as a panel, which enables tracking individuals over time and across cohorts. In total, there are around 140 million observations in the LISA dataset.

III.C. Survey Data

To further examine potential mechanisms, I complement with annual, individual-level survey data from the so-called *SOM* survey.[2] The survey takes the form of a paper questionnaire, and I use data from 1986 to 2019.[3] The questions survey respondents' views on politics and media, and includes several questions related environmental policy. Respondents are randomly selected from the Swedish adult population (aged 16–85). The sample size is large: over 100,000 individual responses are available for the full 1986–2019 period, although not all questions are posed to every respondent. This enables a breakdown of responses at the municipality level, allowing individual responses to be matched with municipality-level data on Chernobyl fallout exposure. It is also possible to examine whether responses differ depending on the age of the respondent, as well as to include demographic controls such as gender, education level, and parental country of birth. Of particular interest for this paper are two questions in the survey, namely whether the respondent supports investments in environmentally-friendly techniques, and whether the respondent is worried about environmental degradation, both being asked on a 1–4 or 1–5 Likert scale.

III.D. Newspaper Data

Finally, the paper utilizes newspaper data from the National Library of Sweden. These data consist of digitized print versions of all national and local newspapers from 2013 to 2019, with 2013 being the first year for which there is complete data availability. For each of the 284 municipalities, I match the most recently available information on the most widely circulated newspaper, and construct an index measuring the average daily number of mentions of the terms "climate change", "cesium" and "Chernobyl" in that newspaper. The index is adjusted for publication frequency, as some newspapers are not published daily (e.g., weekdays only), and is then standardized to have a mean of zero and a standard deviation of one.

[2]Shorthand for *Samhälle, Opinion, Medier* ("Society, Opinion, Media").

[3]The 1986 survey, which was the first one, was sent to households in October 1986, six months after the Chernobyl accident.

IV. Empirical Strategy and Results

This section presents the empirical strategy and main results. I begin by estimating the long-run effects of Chernobyl fallout on green innovation at the municipality level, exploiting cross-municipality variation in exposure to radioactive fallout. I then examine whether these effects reflect changes in the quality of innovation by analyzing patent citations, and use individual-level wage outcomes across sectors and fallout levels to further quantify the economic significance of the Chernobyl-induced green innovation.

IV.A. Municipality-Level Results

1. *Event-Study Estimates*

I begin by analyzing the effect of fallout on the number of green and total patents per capita, as well as the share of green patents of all patents. Since the time period covered is long, starting in 1967 and ending in 2021, I divide the patent sample into five-year intervals. Thus, the first interval cover the years 1967–1971, followed by 1972–1976, 1977–1981, and so on. I then estimate the following fixed-effects model:

$$\text{Green patent per capita}_{it} = \beta_0 + \sum_{t \neq 1982} \beta_t \left(\text{Fallout}_i \times I_t\right) + \gamma_t + \eta_i + \varepsilon_{it} \quad (1)$$

The baseline period, 1982–1986, is excluded for comparison, which in the above specification is denoted by its starting year for compactness. In addition, Green patent per capita$_{it}$ is the number of green patents per capita for municipality i at time t, β_0 is a constant, Fallout$_i$ is the standardized ground deposition of cesium in the municipality, which is interacted with the corresponding period dummies, denoted I_t, γ_t is a time period fixed effect, η_i is a municipality fixed effect, and ε_{it} is an idiosyncratic error term. The outcome is defined as $\log(1+\#\text{green patents})-\log(\text{population})$ to accommodate zero patent counts while allowing coefficients to be interpreted as semi-elasticities of green patenting per capita. To account for spatial correlation across municipalities, I use Conley (1999) standard errors, which allow for spatially dependent residuals.

Figure 3 presents the event-study plots. The top panel shows the year-by-year results when considering the number of green patents per capita, while the bottom panel illustrates the total number of patents per capita for comparison. For the green patents, although the share of green patents per capita increases slightly after 1986, the coefficient estimates are statistically insignificant for the first periods after the accident. Starting with the 2007–2011 period, the estimates increase in magnitude, and the coefficients are significant at the 1% level. For the total patents, the coefficient estimates are close to zero for all time periods. Table A.2 of Online Appendix A presents the numerical estimates for green patents per capita, as well as for total patents per capita. Numerically, the coefficient estimates suggest that one standard deviation of fallout increases the number of green patents per capita by around 12% standard deviations.[4]

The increase of approximately 12% for the three final time periods may also be expressed in terms of the additional green patents. Over the entire period from 2007–2021, there were 8,144 green patents filed. Combining the estimated 12% increase in green patents per capita per standard deviation of fallout with with approximately 17% of the population residing in above-average fallout areas and an average exposure of 1.50 standard deviations implies an increase of about 3.1% in national green patenting. Thus, the estimates imply roughly 250 additional green patents attributable to fallout exposure.

Visually, there is no clear violation of the parallel trends assumption in the event-study figures. To test this more formally, I apply the method proposed by Rambachan and Roth (2023) which provides a framework for assessing the robustness of event-study or difference-in-differences estimates to violations of parallel trends. Specifically, their method allows for bounded deviations from the parallel trends assumption by specifying a parameter M which captures the maximum allowable difference in pre-treatment trend slopes between treated and control units. I set different values of M using the observed pre-treatment trend differences and report "honest" confidence intervals for the treatment effect that account for possible violations within this bound. The maximum value of M is set to be more than three times larger than the magnitude of the observed pre-trend shift.[5] Figure A.1 of Online Appendix A presents the adjusted confidence intervals for various values of M for the first significant post-period, that is, the 2007–2011 period. The results confirm that the post-treatment effect on green patenting remains robust even under severe violations of the parallel trends assumption, suggesting that the main findings are not driven by pre-existing differences in outcome trends.

As a robustness check, Table A.3 of Online Appendix A reports the numerical estimates for green and total patents per capita when applying population weights; the results are robust to to this change, with the coefficient magnitudes being almost identical to those obtained without weights.

2. *Economic Impact*

To quantify the economic magnitude of the estimated effects, I provide a back-of-the-envelope calculation. Note that this calculation is intended to illustrate the economic magnitude of the induced green innovation and should not be interpreted as a comprehensive welfare assessment of the accident.

[4] Because the outcome is defined as $\log(1 + \text{Green patents}) - \log(\text{Pop})$, coefficients are interpreted as semi-elasticities of (1 + green patents) per capita. Imputing the lowest estimated post-1986 coefficient, which is 0.117 for the 2012–2016 period, we have $100 \times e^{(0.117} - 1) \approx 12.41\%$.

[5] This calculation, as well as additional details about the method, is presented in Section C.A of Online Appendix C.

As discussed previously, the estimates imply roughly 250 additional green patents attributable to fallout exposure. To translate this into an economically meaningful estimate, it is useful to note that the literature provides a wide range of estimates for the social value of patents and R&D. At the lower end, C. I. Jones and Williams (1998) present conservative estimates suggesting that the social value is approximately 2–4 times the private value, while B. F. Jones and Summers (2020) estimate social returns of up to 20 times the private value. As a midpoint estimate, Nordhaus (2004) estimates social returns to be slightly above an order of magnitude larger than private returns. Estimates of the private value vary substantially across sectors; for example, Schankerman (1998) estimate the average private value of a patent to be between $4,000 and $70,000 in 1980 dollars, which corresponds to approximately $15,000–$275,000 in 2026 dollars. There is also a premium for green innovations, with Dechezleprêtre et al. (2014) estimating that green innovations receive around 40–43% more citations than brown patents.

Thus, assuming a conservative estimate of $50,000 in private value of a patent, an order of magnitude higher total social value, and that green patents generate 50% higher social value than brown patents, this implies an incremental value of $250,000 per green patent. In turn, this yields an incremental value of induced green innovation of about $63 million. Using alternative incremental values of $50,000–$500,000 per green patent yields a range of $13–$125 million.

IV.B. Citations

Patent counts are primarily a measure of quantity, not quality. Therefore, a natural concern is that the increase in green patenting documented previously reflects a shift in quantity rather than in the technological importance of innovation. To address this, I regress standardized forward citations at the patent level on standardized fallout exposure, an indicator for whether the patent carries the Y02 tag, and the interaction between these two variables. In addition, I estimate an analogous specification where the left-hand side is an indicator for whether a patent falls in the top decile of citations within application year and technology class.

These results are reported in Table 1. First, patents from inventors in fallout-affected areas are slightly more cited, regardless of whether they are green or not; one standard deviation of fallout is associated with 0.008 SD increase in citations. Green patents overall are considerably more cited—the effect is around 0.12 SD for green patents compared to other patents. The interaction between fallout exposure and green patenting is positive, albeit statistically non-significant. For the top-decile indicator, all coefficients are close to zero and statistically insignificant. Taken together, green patents from fallout-affected areas are not of lower quality in any specification, suggesting that the reallocation toward green innovation documented above does not come at the expense of technological relevance. Thus, early-life exposure appears to shape the direction of inventive effort without inducing a trade-off between environmental orientation and innovation quality.

IV.C. Individual-Level Labor Market and Education Outcomes

To complement the innovation results, I turn to the LISA register, which tracks wage income, unemployment spells, study grants, and educational attainment for the full Swedish population annually from 1990 onward. This section focuses on wage income and distinguishes individuals employed in green versus non-green firms, allowing for an assessment of whether the observed reorientation of innovation was accompanied by broader changes in labor market returns.[6] Specifically, I compare wage outcomes between green and non-green sectors within fallout-affected municipalities across time periods.

The results are presented in Table A.4 of Online Appendix A. First, I find no evidence of a broad wage effect associated with fallout. However, during the initial period of increased green patenting (2007–2011), wages in green sectors rise slightly in more exposed municipalities, while no corresponding effects are observed in non-green sectors. The estimated effect on standardized log wages in green sectors is approximately twice as large as that in non-green sectors and is statistically significant at the 10% level. While these estimates are should be interpreted cautiously, they suggest that the shift toward green innovation was not purely symbolic: to the extent that economic returns emerged, they were concentrated in the sectors most directly engaged in green technological activity.

V. Mechanism: Fallout Exposure in Formative Years

The empirical results show a significant shift toward green patenting in fallout-affected municipalities, while overall innovation remained stable. A natural question is what mechanism drives this shift. This section studies the mechanisms underlying the long-run effect of fallout exposure on green innovation and presents evidence consistent with a cohort-based mechanism whereby exposure during formative years reorients future inventors. Section VI then presents corroborating evidence and evaluates alternative explanations.

V.A. Inventor-Level Evidence

1. *Green Inventions and Age at Exposure*

I begin by examining whether a reason for the delayed effect of fallout on green patenting was due to cohort-specific exposure during formative years, such that individuals affected by the disaster and later became inventors have systematically different preferences for

[6] For a definition of sectors classified as "green", see Online Appendix B.

green innovation compared to previous cohorts. To do so, I exploit newly linked administrative data on inventors that include year of birth and municipality of residence, which allows me to identify individuals who were children or adolescents and living in fallout-affected areas at the time of the accident. Given the size of the full patent database and since the inventor data needs to be manually linked to administrative registers, I use a stratified random sample of patents filed between 2007 and 2021. The sample size was chosen to ensure sufficient power to detect a minimum effect size of one percentage point increase in probability of a green patent for each one standard deviation increase in fallout, with at least 80% power and $\alpha = 0.05$. This corresponds to a slope coefficient of 0.01, and resulted in a sample of 1,149 patents, associated with 1,011 unique inventors.[7]

The main specifications in this section use linear probability models, allowing coefficients to be interpreted directly as changes in probabilities and facilitate transparent comparison across specifications. The baseline specification takes the form

$$\begin{aligned}\text{Green}_{imt} = \beta_0 + \beta_1 \text{Fallout}_b + \beta_2 \text{Young1986}_i + \beta_3 \left(\text{Fallout}_b \times \text{Young1986}_i\right) \\ + \mathbf{X}_i' \boldsymbol{\delta} + \gamma_t + \varepsilon_{imt} \qquad (2)\end{aligned}$$

where Green_{imt} is an indicator equal to one if inventor i in municipality m files a green patent in year t, Fallout_b measures standardized cesium fallout in 1986 in the inventor's municipality of residence (b) at that time, Young1986_i is an indicator for being under age 20 at the time of the accident, $\boldsymbol{X}_i$ is an optional vector of individual-level controls, γ_t denotes year fixed effects, and ε_{imt} is the error term. Standard errors are clustered at the municipality level.

Table 2 reports these results. Column (1) shows a positive association between fallout exposure and green patenting when cohort information is not taken into account. Column (2) shows that being under age 20 in 1986, by itself, is not predictive of green innovation. Column (3) introduces the interaction between fallout exposure and childhood exposure status. The interaction coefficient is positive and statistically significant, indicating that the effect of fallout exposure is concentrated among inventors who were children or adolescents at the time of the accident. Columns (4) and (5) show that these results are robust to adding inventor-level controls and inverse probability weights that account for the stratified sampling design.[8] As a robustness check, we may estimate an equivalent

[7] Section C.B of Online Appendix C provides further details.

[8] This is done by adjusting the weight placed on each observation to account for the true share of green patents in the inventor's home municipality.

logit estimates. This model can be written

$$\begin{aligned}\Pr(\text{Green}_{imt} = 1) = \Lambda\Big(&\beta_0 + \beta_1 \,\text{Fallout}_b + \beta_2 \,\text{Young1986}_i \\ &+ \beta_3 \,(\text{Fallout}_b \times \text{Young1986}_i) + \mathbf{X}_i'\boldsymbol{\delta} + \gamma_t + \varepsilon_{imt}\Big) \qquad (3)\end{aligned}$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. Table A.5 of Online Appendix A reports these results, yielding the same conclusions as when using a linear probability model.

We may also use the logit model to estimate the marginal effects by age of exposure, which allows for a slightly more granular age analysis. Figure 4 shows a marginal effects plot depending on age group. These estimates suggest that the marginal effect of fallout on the probability of green patenting is relatively stable across age groups for individuals exposed before age 20, with the largest point estimate observed for the middle childhood (ages 6–10) group. The marginal effect declines for exposure after age 20 and is statistically indistinguishable from zero for cohorts exposed in adulthood. This pattern is consistent with recent findings by Berggren et al. (2026), who show that shocks during formative years have the strongest long-term effects when they occur in middle childhood, while exposure after age 25 has little persistent impact. Taken together, the individual-level estimates and cohort patterns indicate that early-life exposure to environmental risk is associated with a persistent reorientation of inventive activity toward green technologies.

2. *The Probability of Becoming a Green Inventor*

The results established above illustrate that inventors who were below age 20 and lived in fallout-exposed areas were over-represented in green inventions in the early 2000s. However, an important remaining question is whether these cohort results reflect entry into green innovation or instead arise from subsequent switching by established inventors. If the former is correct, we would expect early-life exposure to influence also the initial direction of inventive careers. To assess whether this is the case, I examine whether an inventor's first patented invention is classified as green. Using the same linked inventor-level data, I construct an indicator variable equal to one if an individual's first observed patent is green. The empirical specification mirrors the main inventor-level analysis, relating the probability that an inventor's first patent is green to fallout exposure in the municipality of residence in 1986, an indicator for being under age 20 at the time of the accident, and the interaction between these variables.

The results of the linear probability model are reported in Table 3. These results are similar to the earlier findings; inventors who were exposed to higher levels of fallout during childhood are significantly more likely to enter the patent system with a green invention. The interaction between fallout exposure and childhood exposure is positive and significant across specifications, indicating that the effect is not driven by general age or location differences. Note that the sample size in Table 3 is slightly smaller than the total number of inventors in the dataset, which was 1,011—this is due to the exclusion of inventors who had their first patent before 1986.

Figure 4 provides a nonparametric visualization of these cohort results. The figure plots the probability of the first patent being green by birth cohort, separately for municipalities above and below the 75th percentile of fallout exposure. Birth cohorts are grouped into three-year bins, and the series are smoothed using a three-cohort moving average. The vertical dashed line marks the cohort aged 19 in 1986. Cohorts exposed during childhood and adolescence exhibit an increase in green innovation in more exposed municipalities, while no comparable divergence is observed for cohorts who were already adults at the time of the accident. The divergence emerges only for cohorts young enough to have been exposed prior to entering the innovation system. Figure A.2 of Online Appendix A replaces the 75th percentile of fallout exposure with the 90th; these results are even more pronounced, suggesting that the shift toward green innovation is strongest among inventors from the most heavily exposed municipalities.

Taken together, these results indicate that early-life exposure affects the initial orientation of inventor's careers rather than inducing later switching among established inventors. This gives further evidence to the interpretation that formative experiences shape long-run innovation trajectories, and is consistent with a cohort-based mechanism influencing the direction of technological change.

V.B. Theoretical Model

This section presents a simple model that rationalizes how early-life exposure to environmental risk can lead to a persistent shift in the direction of innovation. The framework illustrates how formative experiences generate preferences that influence the direction of innovation later in life, and matches the empirical design.

1. *Setup*

Time is discrete. Individuals live for two periods: a formative period (childhood) and a working period (adulthood). In adulthood, individuals can become inventors and allocate effort toward developing either green technologies (G) or brown technologies (B). Assume that inventors allocate their fixed innovation effort between green and brown technologies, and let $e_i^G \in [0, 1]$ denote the share of effort allocated to green innovation, and $e_i^B = 1 - e_i^G$ the share allocated to brown innovation, so that total effort is $e_i = e_i^G + e_i^B$. Also, let $\pi_G(t)$ and $\pi_B(t)$ denote the market returns to green and brown innovation, respectively; these returns may change over time, but for simplicity of notation, I drop the time subscript.

Now, let each inventor i have an individual preference for green innovation $\phi_i = \bar{\phi}_i + \lambda_i F_i Y_i$, where $\bar{\phi}_i$ is the baseline motivation to engage in green innovation, λ_i is a sensitivity parameter capturing individual responsiveness to early-life exposure, F_i is exposure to environmental risk (in this case, fallout), and $Y_i = 1$ if the inventor was in their formative years during the disaster, say, age 20 to align with the empirical specification, and zero else. The parameter $\bar{\phi}_i$ is positive for some individuals—reflecting a baseline interest in green innovation—and negative for others, implying indifference or a preference for brown technology. These preferences are assumed to be formed during the formative period and to remain fixed thereafter; in Section VI, I provide direct survey evidence consistent with this persistence by showing that pro-environmental attitudes among exposed cohorts do not systematically evolve over time.

The cost function $c(e_i; h_i)$ is a function of each inventor's human capital h_i, with higher levels of human capital decreasing the cost of effort. We may interpret h_i as a general inventive ability, reflecting the inventor's skills, education, and experience rather than green-specific expertise. For simplicity, I set $c(e_i; h_i) = e_i^2/2h_i$.

2. *Inventor's Maximization Problem*

Formally, the inventor solves

$$\max_{e_i^G \in [0,1]} \quad e_i^G(\pi_G + \phi_i) + (1 - e_i^G)\pi_B - \frac{1}{2h_i}\left[(e_i^G)^2 + (1 - e_i^G)^2\right]$$

Taking the derivative with respect to e_i and setting it equal to zero yields:

$$\frac{\partial U_i}{\partial e_i^G} = (\pi_G + \phi_i - \pi_B) - \frac{1}{h_i}\left(e_i^G - (1 - e_i^G)\right) = 0.$$

Solving for e_i and substituting back the expression for the motivation parameter gives the optimal effort allocated to green innovation:

$$e_i^{G*} = \frac{1}{2} + \frac{h_i}{2}(\pi_G - \pi_B + \bar{\phi} + \lambda_i F_i Y_i). \tag{4}$$

And since total effort is fixed, the effort allocated to brown innovation is

$$\begin{aligned} e_i^{B*} &= 1 - e_i^{G*} \\ &= \frac{1}{2} - \frac{h_i}{2}(\pi_G - \pi_B + \bar{\phi} + \lambda_i F_i Y_i) \end{aligned} \tag{5}$$

In the model, patent counts are interpreted as a monotone function of innovative effort, so that higher aggregate green effort translates into more green patent filings.

3. *Implications for Aggregate Innovation*

Equations (4)–(5) characterize inventors' technological orientation. The preference shifter $\lambda_i F_i Y_i$ tilts the optimal allocation e_i^{G*} toward green innovation for exposed individuals, while total effort is fixed. Thus, the individual-level mechanism affects the composition of inventive activity across technologies, not the overall level of innovation. To aggregate these orientations, let municipalities be indexed by m and time by t, and let $\mathcal{N}_{mt}$ denote the set of active inventors in municipality m at time t, with mass N_{mt}. Aggregate green innovation is

$$G_{mt} \equiv \int_{i \in \mathcal{N}_{mt}} e_i^{G*}\, di,$$

and the average green orientation among active inventors is

$$\bar{e}_{mt}^{G} \equiv \frac{1}{N_{mt}} \int_{i \in \mathcal{N}_{mt}} e_i^{G*}\, di,$$

so that $G_{mt} = N_{mt}\bar{e}_{mt}^{G}$.

In the model, innovation dynamics arise from cohort replacement. Suppose that in each period a fraction δ of inventors exits the innovation system and is replaced one-for-one by entrants, so that $N_{m,t+1} = N_{mt} \equiv N_m$. Let $\mathcal{I}_{mt}$ denote incumbents who remain active and $\mathcal{E}_{mt}$ denote entrants, with $|\mathcal{I}_{mt}| = (1-\delta)N_m$ and $|\mathcal{E}_{mt}| = \delta N_m$. Define the average green orientation among entrants as

$$\bar{e}_{mt}^{G,E} \equiv \frac{1}{|\mathcal{E}_{mt}|} \int_{i \in \mathcal{E}_{mt}} e_i^{G*}\, di,$$

where e_i^{G*} is given by equation (4). Then, the evolution of average green orientation follows directly from aggregation:

$$\begin{aligned} \bar{e}_{m,t+1}^{G} &= \frac{1}{N_m} \int_{i \in \mathcal{N}_{m,t+1}} e_i^{G*}\, di \\ &= (1-\delta)\bar{e}_{mt}^{G} + \delta \bar{e}_{mt}^{G,E}, \end{aligned}$$

where the second line uses that incumbents constitute a fraction $(1-\delta)$ of active inventors and entrants a fraction δ, and where exit is assumed orthogonal to e_i^{G*}. This law of motion implies that municipality-level innovation evolves through cohort replacement rather than through reallocation by incumbent inventors. As cohorts exposed to environmental risk during childhood enter the innovation system, the average orientation of inventive effort shifts toward green technologies in more exposed municipalities. Because individual total effort is fixed and entry offsets exit, this mechanism reorients the composition of innovation without affecting its overall volume. The delayed emergence of aggregate effects follows directly from the age structure of entry into invention. The model rationalizes for the main empirical findings by showing how early-life exposure affects who enters green innovation, producing delayed changes in innovation direction without changes in total patenting.

VI. Corroborating Evidence, Alternative Explanations, and Robustness

This section provides additional evidence for the cohort mechanism using survey data. This is presented in Section VI.A. Then, Section VI.B uses a combination of newspaper and survey data to assess the plausibility of the main alternative channel, namely that the broader salience of environmental discourse during the 2000s disproportionately affected Chernobyl-exposed areas, reactivating latent concerns or memories and thereby shifting inventive behavior. Finally, Section VI.C provides a number of robustness checks, and excludes additional alternative mechanisms.

VI.A. Corroborating Evidence from Survey Data

To better understand the behavioral mechanisms behind the observed increase in green innovation, I utilize the survey data described in Section III.C, which captures environmental attitudes and preferences at the individual level across municipalities. These data provide insight into how Chernobyl fallout exposure impacted public sentiment. In particular, the results from the survey may assist in disentangling whether childhood exposure to fallout shaped later-life attitudes toward environmental risks and investments. Because the survey contains detailed individual-level data—including information on respondents' ages, municipalities of residence, and environmental preferences—it allows us to directly test whether the increase in green innovation was driven by cohorts exposed during their formative years.

1. *Views on Green Technology and Nuclear Power*

I begin by examining respondents' views towards green technologies and environmental policy. I focus on two outcomes. First, whether the respondent is *very supportive* or *somewhat supportive* of investing public funds in green technology, second, whether the respondent reports a positive view of nuclear power, and third, whether the individual is a member of an pro-environment organization. The empirical strategy closely follows the approach used for the inventor data. Since the survey records respondents' year of birth, I construct $Young1986_i$, an indicator equal to one if individual i was below 20 years of age in 1986 and zero otherwise. I estimate the following linear probability specification:

$$Y_{imt}^k = \beta_1^k \text{Fallout}_m + \beta_2^k \text{Young1986}_i + \beta_3^k \left(\text{Fallout}_m \times \text{Young1986}_i\right) + \gamma_t^k + \eta_m^k + \varepsilon_{imt}^k, \quad (6)$$

where Y_{imt}^k denotes outcome k for respondent i in municipality m interviewed in survey wave t, and equals one if the respondent supports green investments (for the first outcome), if the respondent reports a positive view of nuclear power (for the second outcome), and if the respondent is a member of a pro-environment organization (for the final outcome). The coefficient of interest is β_3^k, which captures whether exposure to fallout during formative years is associated with differential policy preferences in adulthood.

The estimated coefficients are presented in Table 4; column (1) estimates only the impact of fallout ($\hat{\beta}_3$), while column (2) gives the results for the full specification. For the question about green investments, one standard deviation higher exposure to fallout is associated with around 0.2% lower support for environmental investments. However, those below age 20 in 1986 are around 0.3% more likely to support environmental investments regardless of fallout exposure, while the interaction term between fallout exposure and whether the respondent was below age 20 at the time of the accident is also positive and close to 0.5% in magnitude. All coefficients are statistically significant.

For the question about nuclear power, attitudes toward are more nuanced. For the full specification in column (2) of Table 4, the coefficients for fallout and whether the respondent was below age 20 in 1986 are both negative in magnitude. However, those exposed to high levels of fallout as children seem to more supportive of nuclear power, although the coefficient is statistically insignificant. Finally, when considering activity in environmental organizations, the estimated interaction between fallout exposure and being below age 20 in 1986 is close to zero. Table A.6 Online Appendix A of reports the estimated odds ratios from a logit model in lieu of an linear probability model, which yields results that are similarly interpreted.

As a robustness check, I augment specification the above with a set of individual-level controls, including gender, education, employment status, and whether the respondent's parents grew up abroad. Because the main identifying assumption is that Chernobyl fallout affected municipalities as good as randomly, the inclusion of these controls should not materially affect the estimates. The results are reported in Table A.7 of Online Appendix A; the coefficient estimates are very similar to the baseline, and all conclusions discussed above remain robust.

2. *Testing Model Predictions*

The theoretical framework outlined in the paper predicts that early-life exposure shifts individuals' underlying preference for green innovation, captured by a durable increase in the parameter $\phi_i = \bar{\phi} + \lambda_i F_i Y_i$. This shift is "sticky"—once formed during formative years, it persists independently of later market returns (π_G) or discourse. To test this prediction of preference persistence, we may utilize the individual-level survey data. If the mechanism operates through sticky preferences, there should not be a change over time in pro-green attitudes (e.g., support for investments in environmentally-friendly techniques) among the exposed young cohorts. A time-dependent effect would instead suggest preferences change over time as a result of contemporaneous climate discourse. To test this, I estimate

$$\begin{aligned}
Y^k_{imt} = \beta_0 &+ \beta^k_1 \text{Fallout}_m + \beta^k_2 \text{ExposedCohort}_j \\
&+ \beta^k_3 (\text{Fallout}_i \times \text{ExposedCohort}_j) \\
&+ \beta^k_4 (\text{Fallout}_i \times \text{ExposedCohort}_j \times \text{YearsSince}_{jt}) \\
&+ \mathbf{X}'_i \boldsymbol{\delta} + \gamma_t + \varepsilon_{ijt}. \qquad (7)
\end{aligned}$$

where YearsSince is the number of years that have passed since the accident. The results are presented in Table A.8 of Online Appendix A. The estimated coefficient $\widehat{\beta}_3$ is positive and significant, consistent with the exposed cohort expressing more favorable views toward green innovation. Importantly, $\widehat{\beta}_4$ is small and statistically insignificant. This indicates that the attitude differential for the exposed cohort does not systematically strengthen or fade over the three decades following the accident. The absence of a significant time trend supports the interpretation that early-life exposure induced a durable ("sticky") shift in preferences that remains stable as the cohort ages, rather than a transient response or one amplified by later climate discourse.

VI.B. Alternative Explanation: Differential Climate Discourse

1. *Newspaper Data*

One potential alternative channel that may explain the delayed effect on green innovation is that the rise in green innovation in fallout-affected areas was not due to early-life exposure of new inventors, but rather a disproportionate response of fallout-exposed areas to the broader increase in the policy relevance of environmental issues during the early 2000s. Under this channel, global developments in the first decades of the 21st century, such as Al Gore's 2006 film *An Inconvenient Truth*, the 2007 IPCC reports, and a general increase in media attention to climate change in the early 2000s, may have interacted with the historical memory of Chernobyl. In turn, this may have caused environmental concerns to become disproportionately more salient in fallout-affected municipalities, leading inventors in these areas to shift toward green innovation. To evaluate this mechanism, I turn to the 2013–2019 newspaper data described previously, and count occurrences of the word "climate change" in each municipality's most widely circulated newspaper, adjusted for publication frequency.

Besides evaluating the alternative discourse-based mechanism, newspaper data can shed additional light on the cohort-based mechanism. This is because the cohort-based interpretation requires that those who were in their formative ages in 1986 were aware of the fallout levels in their home municipality. If local exposure was not publicly reported at the time, or if it faded entirely from memory, it would be difficult to explain a behavioral response decades later. To evaluate both of these channels, I also count occurrences of the words "cesium" and "Chernobyl" in addition to "climate change". Even though 1986 newspaper data is not available, if coverage of "cesium" and "Chernobyl" remained higher decades later, it is highly likely they also experienced higher levels of reporting at the time of the disaster, increasing the plausibility of a cohort-based channel.

The results are reported in Table 5. Column (1) shows results for all 284 municipalities; column (2) excludes municipalities whose leading newspapers have nationwide coverage, leaving a sample of 242 municipalities to reduce possible bias from large science or national news sections. These findings indicate that municipalities with higher fallout exposure indeed saw significantly more frequent mentions of "cesium" and "Chernobyl". However, there is no corresponding increase in references to "climate change" when removing municipalities where the local newspaper has national coverage. Taken together, these results cast doubt on the salience-based alternative mechanism. If fallout-affected areas had been disproportionately influenced by the rise in environmental discourse during the 2000s, we would expect to see a corresponding increase in local media references to "climate change." The absence of such a pattern suggests that these areas were not disproportionally responsive to environmental reporting by the media.

2. *Further Survey Evidence*

To further distinguish between the cohort-based salience mechanism and an alternative explanation rooted in a general rise in environmental concern during the early 2000s, I return to the survey data. If the observed increase in green innovation was primarily driven by a broader shift in climate concern, we would expect to see a measurable increase in concern about the environment among fallout-exposed individuals in the early 2000s. A question whether the individual worries about "environmental degradation" is in the survey, with responses given on a 1–4 Likert scale, and I examine the impact of fallout interacted with the year dummies on whether the respondent is "very worried" or "somewhat worried", as well as only "very worried", about environmental degradation. The first period for which this question was asked was in the 1987–1991 period, so this is the baseline category in this analysis.

The results are presented in Table A.9 of Online Appendix A. The results show no evidence of such a shift; the estimated coefficients in the linear probability model are all close to zero and statistically insignificant, with the exception of the coefficient for the 1987–1991 period when using both the share of 'very worried" and "somewhat worried". Thus, overall, respondents in fallout-affected municipalities are no more likely to report environmental degradation as a serious concern than those in unaffected areas, and the pattern does not change following the global rise in climate discourse. Thus, these results are inconsistent with the hypothesis that green innovation rose due to a contemporaneous, nationwide increase in climate awareness.

VI.C. Robustness and Exclusion of Alternative Mechanisms

1. *Placebo Test*

As a robustness check, we may conduct placebo tests using classes of patents unrelated to environmental technology. First, I examine the effects of brown (non-green) patents broadly, which is the total number of patents minus patents in the Y02 category. Then, I focus on patents in the A45 category, which includes luggage, umbrellas, handbags, purses, and shaving equipment. These technologies are highly unlikely to be causally influenced by exposure to the Chernobyl fallout. I re-estimate the main municipality-level event study specification, replacing the outcome variable, first, with the number of brown patents per capita, and then, with the number of A45 patents per capita; in total, there were 2,210 patents in this category over the 1967–2021 period.

The results reported in Figure A.3 in Online Appendix A show no significant association between fallout exposure and non-green or A45 patenting in any post-1986 period. This holds even in the post-2000 periods where green patenting increases significantly. These placebo results reinforce the interpretation that the observed rise in green patenting is not driven by overall changes in innovation behavior, but is instead specific to technologies related to environmental concerns. The absence of any effect on A45 patents helps rule out unobserved municipality-level confounders that might otherwise drive an overall rise in innovation.

2. *Out-Migration*

One important concern is that long-run differences in innovation reflect selective migration rather than changes in behavior. To address this, I examine whether fallout exposure affected out-migration at the municipality level, examining both the entire population, as well as the 0–19 subgroup, which are the cohorts that drive the innovation results. The results are reported in Table A.10 of Online Appendix A, divided into the first three years after Chernobyl as well the first ten years after the accident. I find no evidence of increased out-migration in more exposed municipalities. If anything, overall out-migration is slightly lower in higher-fallout areas. These patterns suggest that selective sorting is unlikely to explain the observed cohort-specific effects.

3. *Directed Investment in Affected Municipalities*

Another potential mechanism relates to government spending. Specifically, if the observed shift in innovation was driven by targeted fiscal interventions, such as financial support to fallout-affected municipalities, we would expect to observe differential increases in government transfers to areas more exposed to the Chernobyl fallout. An example of such an intervention would be funding directed toward research in green sectors. While the available data do not provide a detailed breakdown of sectoral allocations, we can examine total government transfers to municipalities as a proxy. Data on these transfers are available starting in the period 1977–1982, which somewhat limits the number of pre-treatment observations available for this variable.

The results in Figure A.4 of Online Appendix A indicate no significant relationship between fallout intensity and changes in government transfers to municipalities following 1986. Government transfers are measured in SEK per capita and standardized to have mean zero and unit standard deviation. Thus, this finding suggests that the increase in green innovation is unlikely to have been a consequence of increased public investment. Instead, it reinforces the interpretation that the shift toward green patenting reflects a behavioral response, in the form of deepened interest among inventors for green innovation.

4. *Inflow of Highly Educated Residents*

One potential alternative channel behind the increase in green patents is a rise in human capital in more exposed areas. Specifically, it is possible that, following the Chernobyl disaster, more individuals pursued higher education—perhaps within STEM fields—which could have facilitated innovation over time. I assess this channel first using municipality-level data, and then turning to individual-level administrative register data.

At the municipality level, Figure A.5 in Online Appendix A presents event-study estimates for the share of residents with at least three years of higher education, including those holding a PhD degree interacted with fallout. The estimates are close to zero and statistically insignificant across all periods, indicating no differential change in educational attainment in more exposed municipalities following the accident.

To complement this aggregate evidence, I then turn to individual-level administrative data from the LISA register. Again, this data is only available from 1990, but provides more granular evidence at the individual-level. The first column of Table A.11 of Online Appendix A reports estimates using the standardized number of weeks of utilized study aid per individual and year since 1990 as a proxy for accumulated academic credits. Consistent with the municipality-level results, there is no evidence of systematic changes in this measure over time, and all estimated effects are close to zero in magnitude. Taken together, these findings suggest that although green patenting increased in municipalities more exposed to Chernobyl fallout, this shift was not driven by increases in educational attainment or human capital accumulation in those areas.

5. *Further Individual-Level Outcomes*

To further assess whether the observed increase in green innovation can be explained by changes in individual economic constraints or family circumstances, I examine a broader set of individual-level outcomes using the LISA register. In addition to the study aid variable analyzed previously, I consider temporary parental benefits for the care of sick children and sickness leave. The results are reported in the two rightmost columns of Table A.11 of Online Appendix A. Across all outcomes, I find no systematic differences between individuals residing in fallout-exposed and non-exposed municipalities, including during the post-2000 period when green innovation rises sharply.

The absence of effects on these margins helps rule out alternative explanations based on changes in education, family structure, or health outcomes. Instead, the results are consistent with a mechanism in which exposure to a major environmental disaster influenced the direction of innovative effort without affecting broader economic or demographic outcomes. Together with the inventor-level evidence and the absence of effects on wages or education, these results are most consistent with a cohort-based mechanism and difficult to reconcile with explanations based on changing incentives or climate discourse.

VII. Concluding Remarks

This paper studies how a major environmental accident can shape the long-run direction of technological change. Exploiting plausibly exogenous variation in radioactive fallout from the 1986 Chernobyl disaster across Swedish municipalities, I show that areas more exposed to fallout subsequently experienced a persistent increase in green patenting, with no corresponding change in non-green innovation or total patenting. Importantly, this effect emerges only from the early 2000s, long after the accident itself, pointing to a delayed response rather than an immediate reallocation of inventive effort.

Linking inventor data with and administrative records, the paper provides evidence consistent with a cohort-based mechanism. Inventors who were exposed to fallout during their formative years are more likely to direct their innovative activity toward green technologies decades later. This pattern is difficult to reconcile with explanations based on incentives, changes in human capital, or differential exposure to climate-related discourse alone. Instead, the findings suggest that early-life exposure to environmental accidents can durably shape preferences that later influence the direction, rather than the volume of innovation. In this sense, the results complement existing work on directed technical change that emphasizes policy and price incentives (e.g., Aghion et al. 2016) by identifying a distinct channel operating through cohort-specific entry into innovation. More broadly, the findings show that historical shocks can shape the technological trajectory of an economy over long horizons, even in the absence of direct policy intervention.

The analysis also contributes to a growing literature showing that formative experiences have long-lasting effects on economic behavior (Malmendier, Tate, et al. 2011). Applied to innovation, this perspective suggests that historical shocks may influence not only how much innovation occurs, but which technologies are pursued and by whom.

More broadly, the results imply that environmental accidents can have unintended and persistent effects on the technological trajectory of an economy through their impact on the composition of the inventor pool.

There are several avenues for future research. One direction is to further exploit individual-level data to more precisely trace how early-life exposure translates into later inventive choices, including the role of education, occupational sorting, and peer effects. Another potential direction is to disentangle the underlying behavioral mechanisms that link formative exposure to later innovation decisions. Understanding these channels would help clarify how large historical shocks shape the evolution of technology over the long run, and how this interacts with policy-driven incentives in directing technological change.

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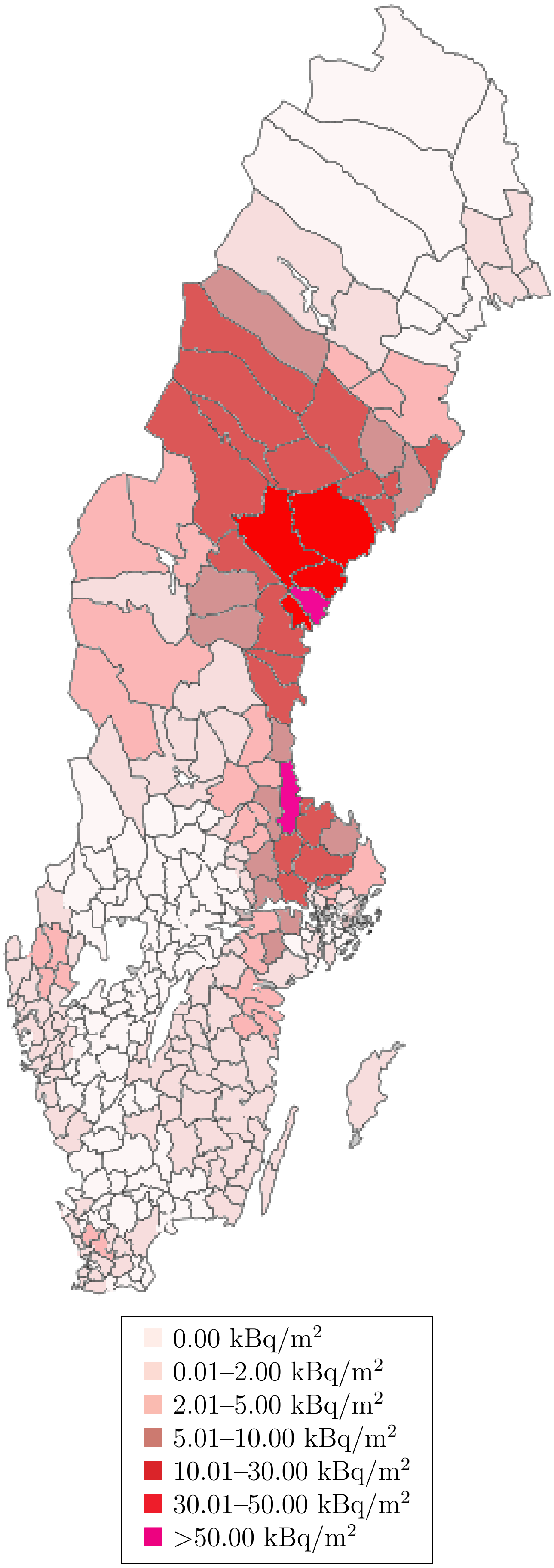


Figure 1: Variation in average ground deposition at the municipality level.

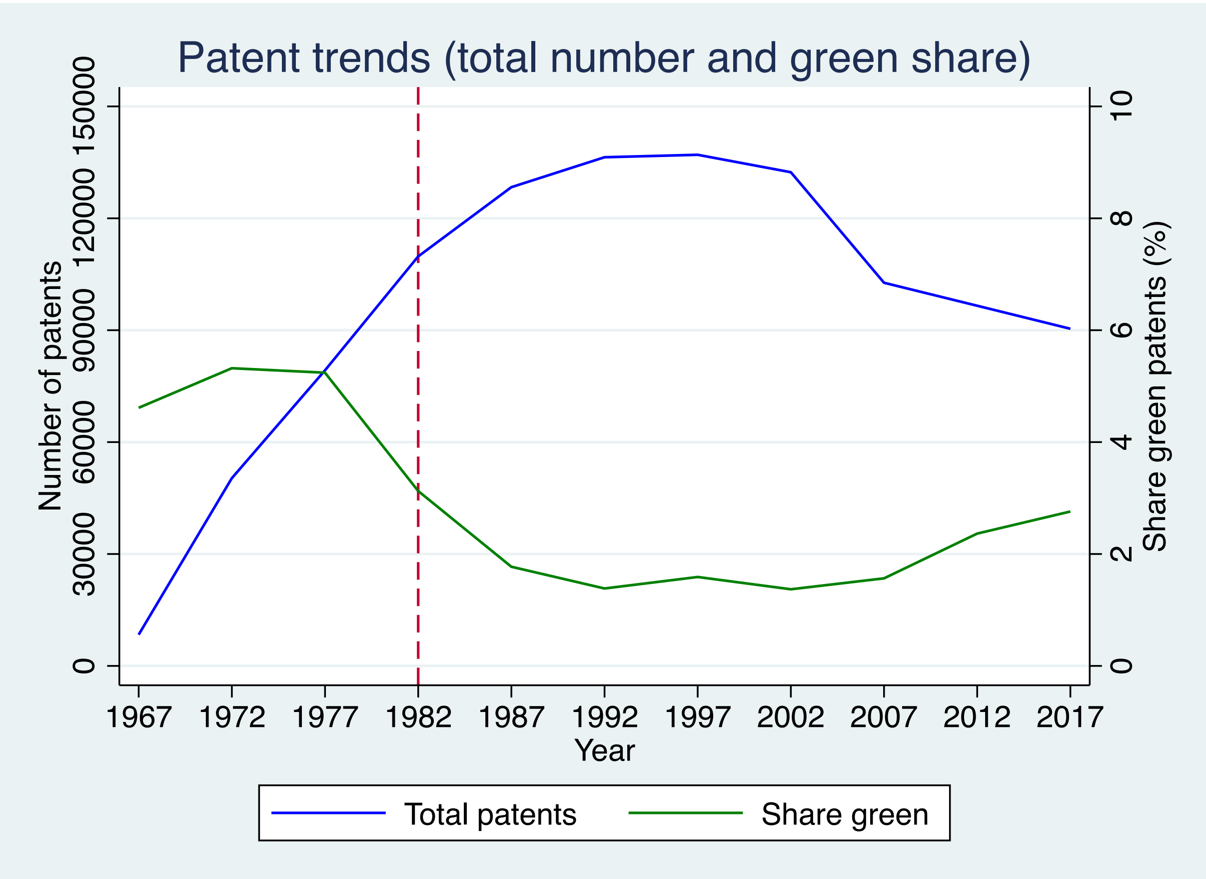
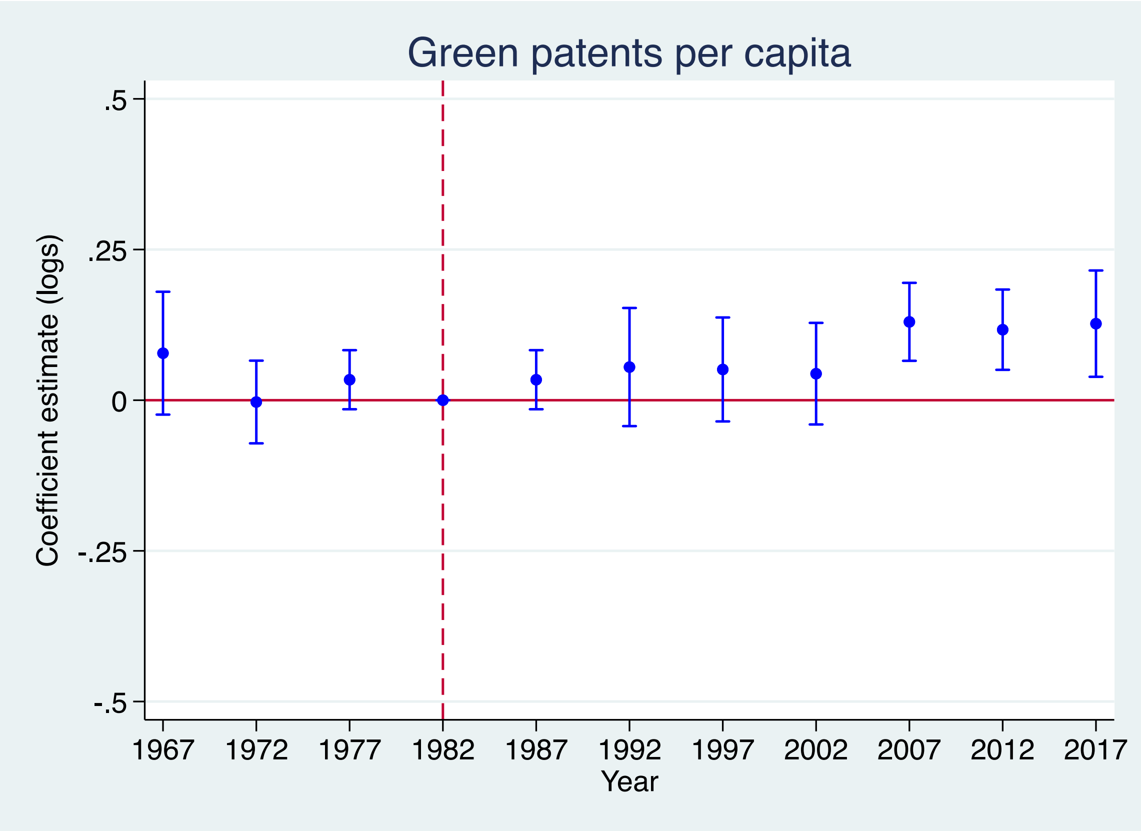
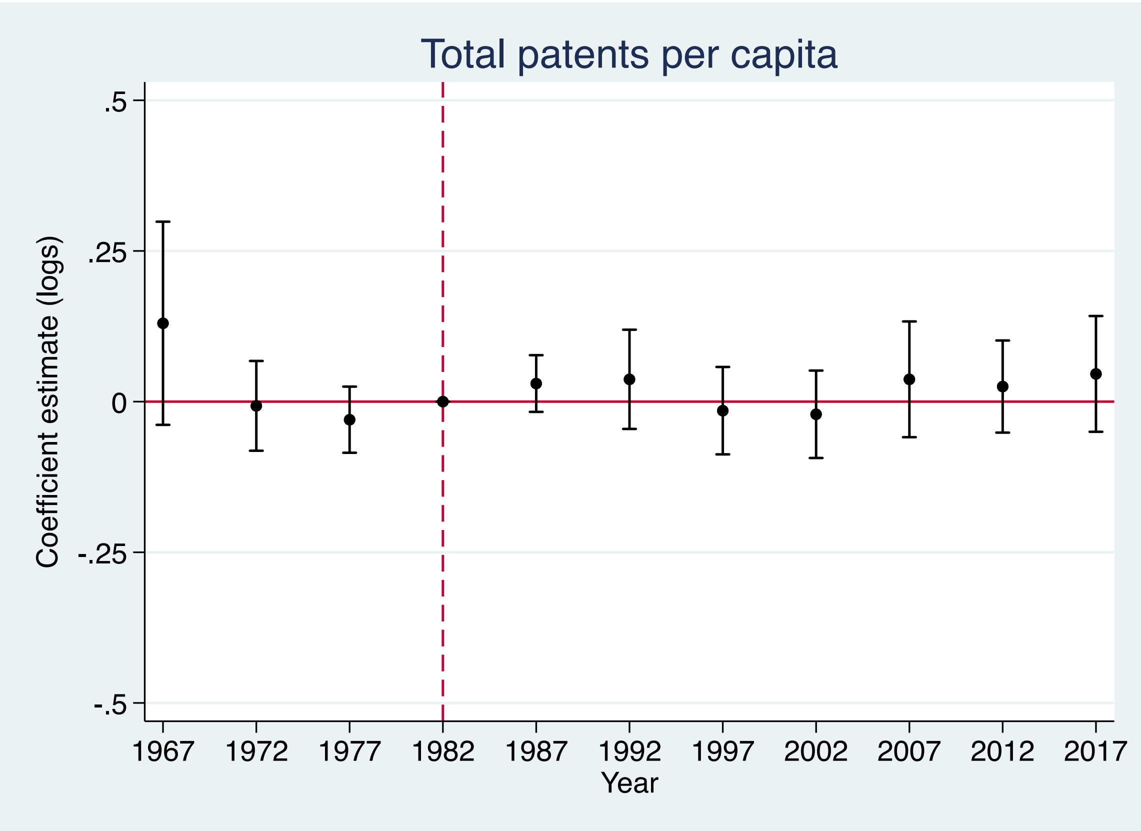


Figure 2: Trends in total patent filings and the share of green patents the from 1967–1971 period to 2017–2021.



(a) Green patents per capita.



(b) Total patents per capita.

Figure 3: Estimated Chernobyl effect on green and total patenting per capita. Panel (a) shows green patents per capita, while Panel (b) shows total patents per capita. The pre-period (1982–1986) is marked by a dashed vertical red line. Shaded areas represent 95% confidence intervals constructed using spatial standard errors.

Table 1
Fallout Exposure, Green Patents, and Citations

	Standardized citations			Top-decile citations indicator		
	(1)	(2)	(3)	(1)	(2)	(3)
Standardized fallout	0.008*		0.008	0.002		0.002
	(0.004)		(0.004)	(0.002)		(0.002)
Green patent		0.123***	0.123***		0.022	0.024
		(0.037)	(0.037)		(0.016)	(0.015)
Std. fallout × Green patent			0.007			–0.002
			(0.007)			(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,077	91,841	91,841	92,077	91,841	91,841
R^2	0.305	0.306	0.307	0.056	0.056	0.056

Note. Columns (1)–(3) report linear regressions with standardized forward citations as the dependent variable. Columns (4)–(6) use an indicator equal to one if a patent is in the top decile of citations within application year and technology class. *Fallout* is standardized cesium fallout in the inventor's municipality of residence in 1986. *Green patent* is an indicator for patents classified as green (CPC Y02). All specifications include application-year and technology fixed effects. Standard errors are clustered at the municipality × inventor level and reported in parentheses.

Table 2
Green Innovation and Formative Exposure to Fallout

Outcome variable: Green patent (dummy)	(1)	(2)	(3)	(4)	(5)
Standardized fallout	0.032***		−0.020***	−0.021***	−0.021***
	(0.006)		(0.007)	(0.007)	(0.007)
Young1986		−0.022	−0.025	−0.023	−0.023
		(0.023)	(0.020)	(0.020)	(0.020)
Standardized fallout × Young1986			0.096***	0.097***	0.097***
			(0.020)	(0.019)	(0.019)
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Weights	No	No	No	No	Yes
Observations	1,148	1,148	1,148	1,148	1,148
Method	LPM	LPM	LPM	LPM	LPM
Mean dep. var	0.134	0.134	0.134	0.134	0.134
R^2	0.030	0.022	0.050	0.054	0.054

Note. Each column reports coefficients from a logit regression. The dependent variable is a dummy equal to 1 if the patent is classified as green (CPC Y02). *Fallout* is standardized cesium fallout in the inventor's 1986 municipality. *Young1986* is a dummy for inventors estimated to be under 20 years old in 1986. Column (5) uses inverse probability weights to correct for stratified sampling of green and non-green patents. Standard errors clustered at the municipality × inventor level in brackets.

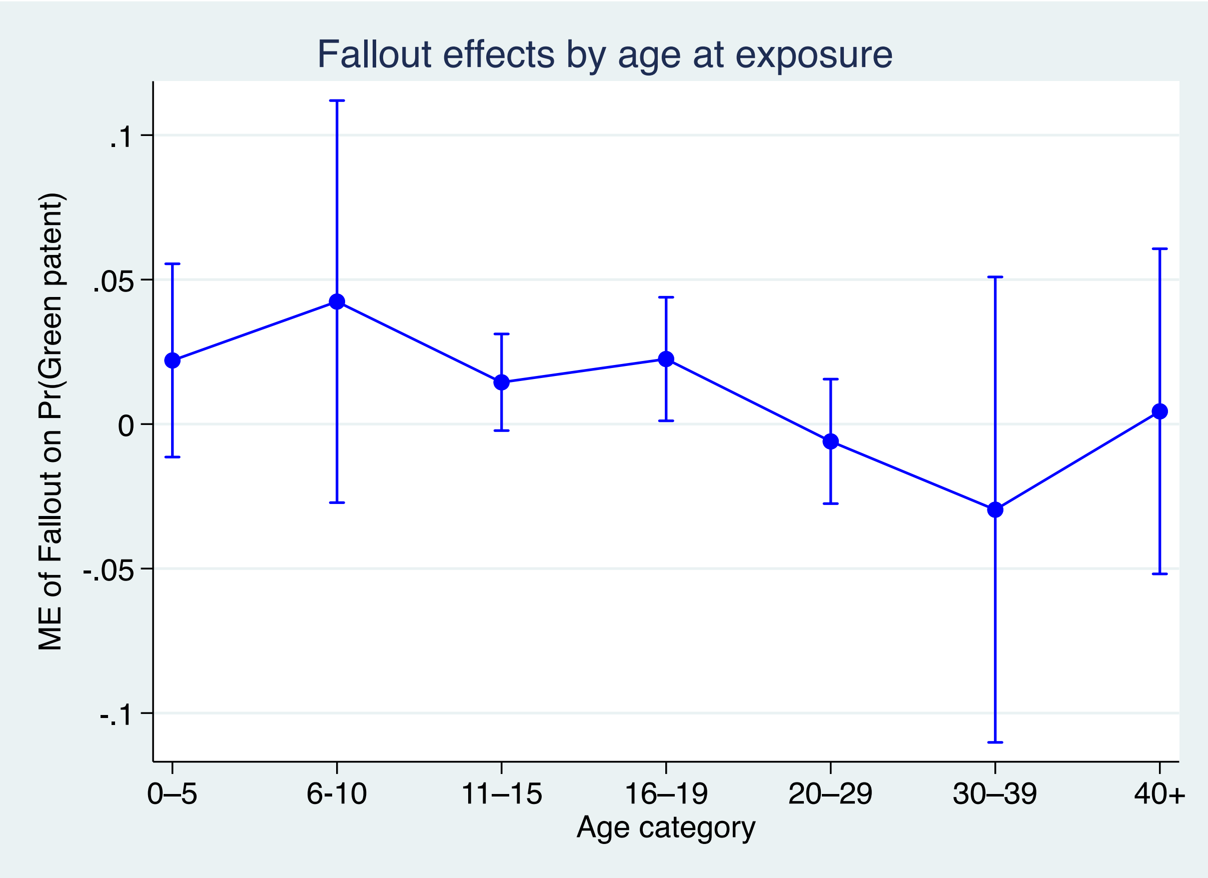


Figure 4: Plot of the average marginal effects of a one–standard-deviation increase in radioactive fallout on the probability that a patent is classified as green, estimated separately by age at the time of the Chernobyl accident.

TABLE 3

FIRST INNOVATION AND FORMATIVE EXPOSURE TO FALLOUT

Outcome variable: First patent is green (dummy)	(1)	(2)	(3)	(4)	(5)
Standardized fallout	0.021*		−0.007	−0.007	−0.007
	(0.012)		(0.007)	(0.007)	(0.007)
Young1986		−0.003	−0.019	−0.019	−0.019
		(0.020)	(0.019)	(0.019)	(0.019)
Standardized fallout × Young1986			0.061***	0.061***	0.061***
			(0.022)	(0.022)	(0.022)
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Weights	No	No	No	No	Yes
Observations	985	985	985	985	985
Method	LPM	LPM	LPM	LPM	LPM
Mean dep. var	0.091	0.091	0.091	0.091	0.091
R^2	0.062	0.049	0.058	0.062	0.062

Note. Each column reports coefficients from a logit regression. The dependent variable is a dummy equal to 1 if the patent is classified as green (CPC Y02). *Fallout* is standardized cesium fallout in the inventor's 1986 municipality. *Young1986* is a dummy for inventors estimated to be under 20 years old in 1986. Column (5) uses inverse probability weights to correct for stratified sampling of green and non-green patents. Standard errors clustered at the municipality × inventor level in brackets.

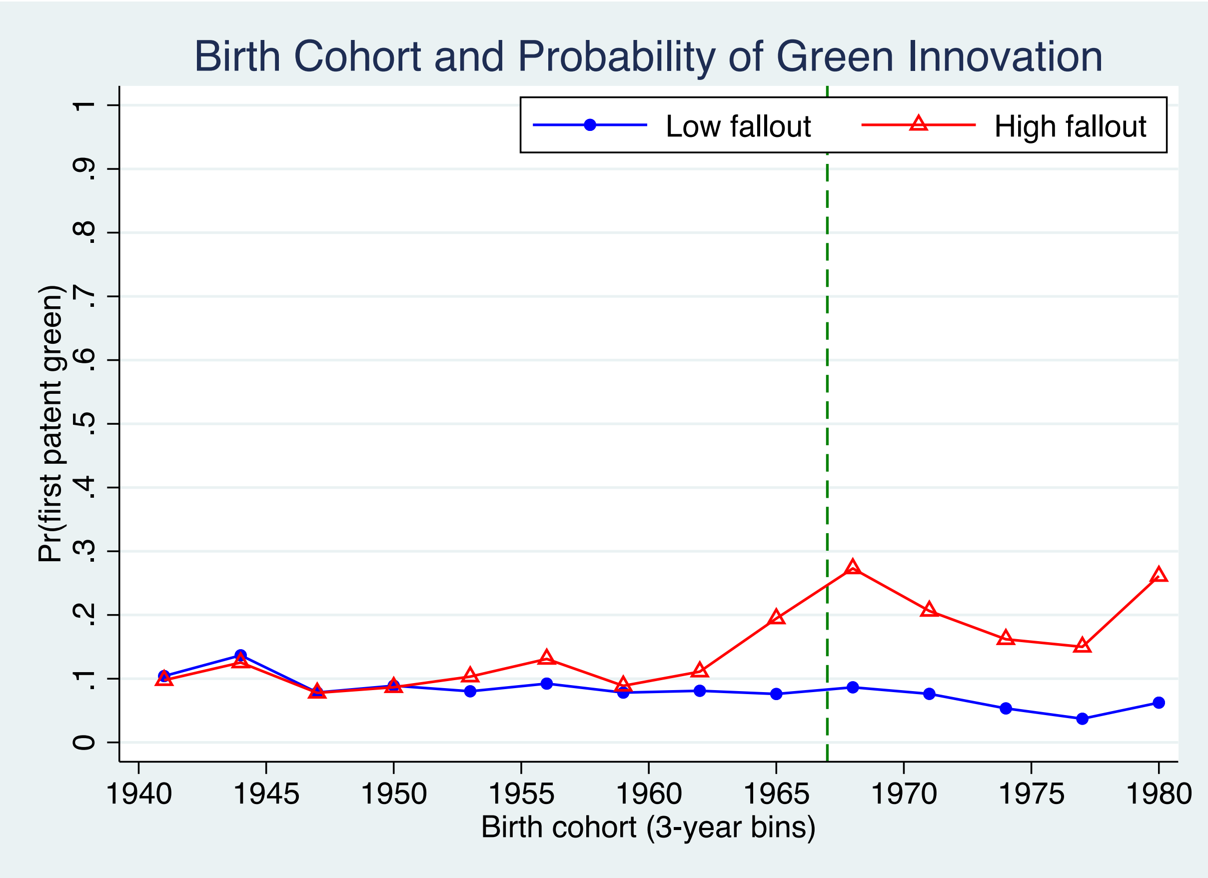


Figure 5: The probability of ever inventing green (y-axis) by birth cohort of inventors (x-axis) and municipality fallout, where "high fallout" is defined as fallout being above the 75$^{\text{th}}$ percentile. Lines are smoothed using a centered three-cohort moving average. The cohort that was 19 years old in 1986 (born in 1967) is marked with a dashed green line.

Table 4
Views on Environmental Investments, Nuclear Power, and Environmental Organization Activity

Outcome variable:	Environm. investments (1 = Positive)		Nuclear power (1 = Positive)		Active in env. org (1 = Yes)	
	(1)	(2)	(1)	(2)	(1)	(2)
Std. fallout	-0.002^{*}	-0.003^{***}	-0.008	-0.011^{*}	-0.001	-0.001
	(0.001)	(0.001)	(0.006)	(0.007)	(0.001)	(0.001)
Young in 1986		0.014^{***}		-0.050^{***}		0.011^{***}
		(0.004)		(0.005)		(0.003)
Std. fallout × Young in 1986		0.005^{*}		0.011		0.001
		(0.003)		(0.007)		(0.002)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,557	119,557	51,652	51,652	102,211	102,211
Method	LPM	LPM	LPM	LPM	LPM	LPM
Mean dep. var.	0.398	0.398	0.423	0.423	0.067	0.067
R^2	0.208	0.208	0.096	0.098	0.003	0.004

Note. Standard errors clustered at the municipality level in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Outcome variable defined in header.

Table 5

Occurrence of Chernobyl-related words in media

Outcome variable:	"Climate change"		"Cesium"		"Chernobyl"	
Cumulative number each word appears in most circulated newspaper	(1)	(2)	(1)	(2)	(1)	(2)
Fallout	-0.082^{***}	0.004	0.151^{***}	0.234^{***}	-0.043	0.050^{***}
	(0.026)	(0.009)	(0.038)	(0.026)	(0.033)	(0.013)
Controls	No	No	No	No	No	No
Only local papers	No	Yes	No	Yes	No	Yes
Observations	284	242	284	242	284	242
Mean dep. var.	0.000	0.000	0.000	0.000	0.000	0.000

Note. Outcome variable: Standardized cumulative number of times the words "climate change", "cesium", and "Chernobyl" appear in the most circulated newspaper in each municipality from January 1, 2013, to December 31, 2019. Column (2) drops municipalities where the largest paper is either *Dagens Nyheter*, *Svenska Dagbladet*, *Göteborgs-Posten*, or *Sydsvenskan*, which have full national coverage. A constant is included in all regressions. Spatial corrected standard errors in brackets. *** denotes significance at the 1% level.

Online Appendix [Not for Publication]

A. Additional Empirical Results

Table A.1
Summary Statistics

Variable	Mean	Std. dev.	Min	Max
Municipality-level variables:				
Green patents per capita	0.0001	0.0003	0	0.0067
Total patents per capita	0.003	0.008	0	0.123
Fallout (kBq/m^2)	3.58	8.20	0	73.52
Newspaper mentions of “Chernobyl” (2013–2019)	92.10	104.96	3	437
Newspaper mentions of “cesium” (2013–2019)	13.83	13.11	0	55
Newspaper mentions of “climate change” (2013–2019)	1,098.98	1,393.23	100	5,856
LISA variables:				
Wage (SEK)				
Working in green sector (binary)	0.018	0.134	0	1
Survey variables:				
Positive towards environmental investments (binary)	0.398	0.490	0	1
Positive towards nuclear power (binary)	0.423	0.494	0	1
Active in an environmental org. (binary)	0.067	0.250	0	1
Worried about environmental degrad. (binary)	0.489	0.500	0	1
Additional variables:				
Log citations	1.572	1.195	0	6.410

Table A.2
Effect of Fallout Exposure on Patent Outcomes by Period

Outcome variable:	Green patents per capita	Total patents per capita
Std. fallout × $I_{1967-1971}$	0.078	0.130
	(0.052)	(0.086)
Std. fallout × $I_{1972-1976}$	–0.003	–0.007
	(0.035)	(0.038)
Std. fallout × $I_{1977-1981}$	0.034	–0.030
	(0.025)	(0.028)
Std. fallout × $I_{1987-1991}$	0.034	0.030
	(0.025)	(0.024)
Std. fallout × $I_{1992-1996}$	0.055	0.037
	(0.050)	(0.042)
Std. fallout × $I_{1997-2001}$	0.051	–0.015
	(0.044)	(0.037)
Std. fallout × $I_{2002-2006}$	0.044	–0.021
	(0.043)	(0.037)
Std. fallout × $I_{2007-2011}$	0.130***	0.037
	(0.033)	(0.049)
Std. fallout × $I_{2012-2016}$	0.117***	0.025
	(0.034)	(0.039)
Std. fallout × $I_{2017-2021}$	0.127***	0.046
	(0.045)	(0.049)
Municipality FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,124	3,124
Mean dep. var.	0.000	0.000

Note. The table reports coefficients from regressions of green or total patenting per capita on fallout exposure interacted with time-period dummies. The omitted category is 1982–1986. All regressions include municipality and time fixed effects. Spatial standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

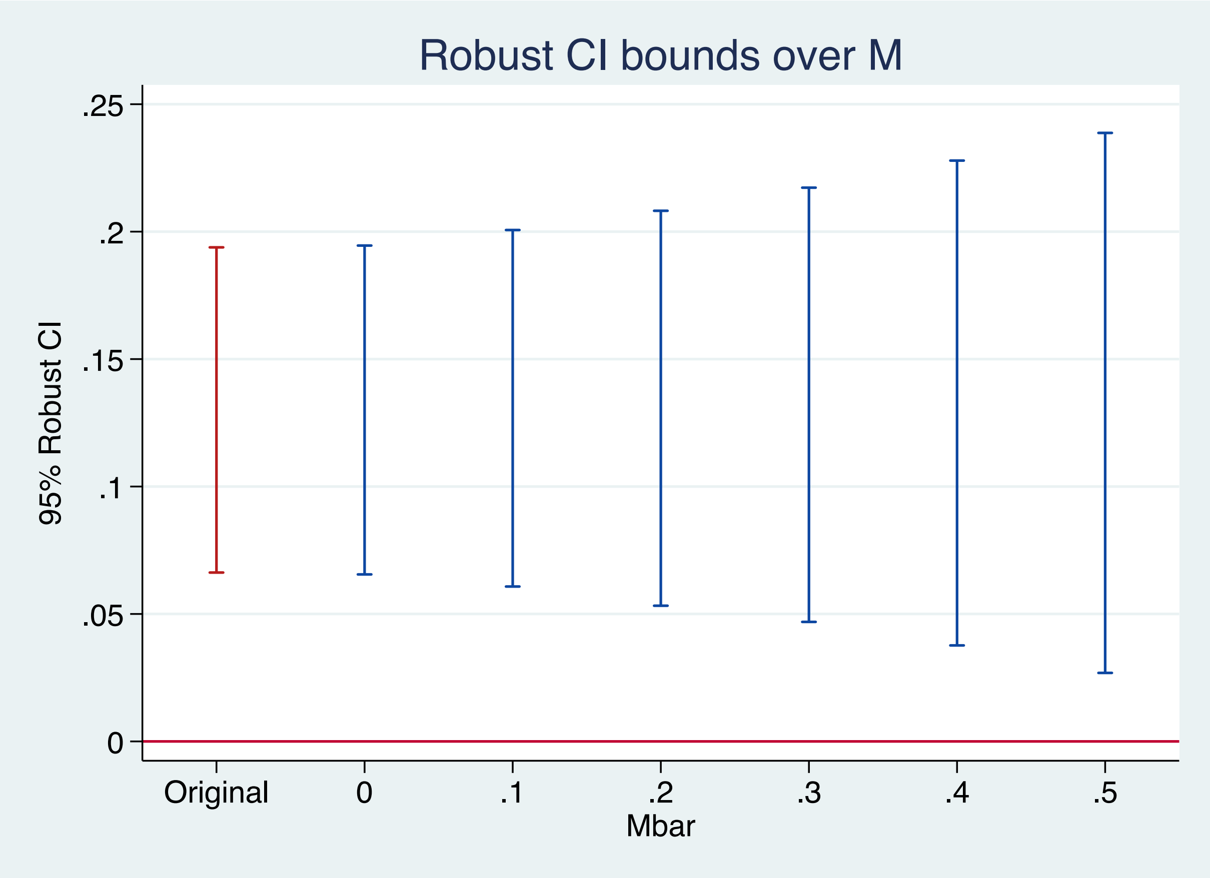


Figure A.1: Rambachan–Roth confidence intervals for the estimates of the Chernobyl effect on the green patents per capita from Figure 2 for the 2007–2011 period, with $M = 0$ corresponding to the original estimates, and $M = 0.5$ representing a pre-trend violation three times larger than the one observed in the pre-period. See Online Appendix C for additional details.

Table A.3
Effect of Fallout Exposure on Patent Outcomes by Period
(Population-Weighted)

Outcome variable:	Green patents per capita	Total patents per capita
Std. fallout × $I_{1967-1971}$	0.077	0.119
	(0.055)	(0.086)
Std. fallout × $I_{1972-1976}$	–0.005	–0.012
	(0.036)	(0.041)
Std. fallout × $I_{1977-1981}$	0.032	–0.036
	(0.025)	(0.030)
Std. fallout × $I_{1987-1991}$	0.035	0.030
	(0.025)	(0.024)
Std. fallout × $I_{1992-1996}$	0.056	0.035
	(0.052)	(0.042)
Std. fallout × $I_{1997-2001}$	0.055	–0.016
	(0.046)	(0.038)
Std. fallout × $I_{2002-2006}$	0.043	–0.024
	(0.044)	(0.038)
Std. fallout × $I_{2007-2011}$	0.133***	0.033
	(0.034)	(0.050)
Std. fallout × $I_{2012-2016}$	0.122***	0.021
	(0.035)	(0.040)
Std. fallout × $I_{2017-2021}$	0.134***	0.041
	(0.045)	(0.049)
Municipality FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,124	3,124
Mean dep. var.	0.000	0.000

Note. The table reports coefficients from regressions of green or total patenting per capita on fallout exposure interacted with time-period dummies. Population-weighted estimates. The omitted category is 1982–1986. All regressions include municipality and time fixed effects. Spatial standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.4
Effect of Fallout Exposure on Log Wages by Sector and Time

Outcome variable:	**Log income (green sector)**	**Log income (non-green sector)**
Std. fallout × $I_{1992-1996}$	–0.008	–0.006
	(0.021)	(0.015)
Std. fallout × $I_{1997-2001}$	0.004	–0.003
	(0.001)	(0.003)
Std. fallout × $I_{2002-2006}$	0.003	0.001
	(0.005)	(0.004)
Std. fallout × $I_{2007-2011}$	0.012*	0.006
	(0.006)	(0.004)
Std. fallout × $I_{2012-2016}$	0.011	0.007
	(0.007)	(0.004)
Std. fallout × $I_{2017-2021}$	0.008	0.006
	(0.006)	(0.005)
Municipality FE	Yes	Yes
Time FE	Yes	Yes
Observations	4,107,458	144,396,889
R^2	0.713	0.718

Note. The table reports coefficients from regressions of individual log annual taxable income on standardized fallout exposure interacted with time-period dummies, separately for workers in green and non-green firms. The omitted category is 1990–1991. All regressions include municipality and time-period fixed effects. Standard errors are clustered at the municipality level. * denotes significance at the 10% level.

Table A.5
Inventor-Level Green Innovation and Formative Exposure to Fallout (Logit)

Outcome variable: Green patent (dummy)	(1)	(2)	(3)	(4)	(5)
Standardized fallout	1.212***		0.779*	0.779*	0.850
	(0.036)		(0.105)	(0.104)	(0.092)
Young1986		0.820	0.739	0.749	0.798
		(0.174)	(0.144)	(0.147)	(0.190)
Standardized fallout × Young1986			1.923***	1.966***	1.731***
			(0.311)	(0.313)	(0.212)
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	Yes	Yes
Weights	No	No	No	No	Yes
Observations	1,158	1,158	1,158	1,158	1,158
Method	Logit	Logit	Logit	Logit	Logit
Coefficient displayed	OR	OR	OR	OR	OR
Mean dep. var	0.134	0.134	0.134	0.134	0.134

Note. Each column reports estimated odds ratios (ORs) from a logit regression. The dependent variable is a dummy equal to 1 if the patent is classified as green (CPC Y02). *Fallout* is standardized cesium fallout in the inventor's 1986 municipality. *Young1986* is a dummy for inventors estimated to be under 20 years old in 1986. Column (5) uses inverse probability weights to correct for stratified sampling of green and non-green patents. Standard errors clustered at the municipality × inventor level in brackets. * and *** denote significance at the 10% and 1% levels, respectively.

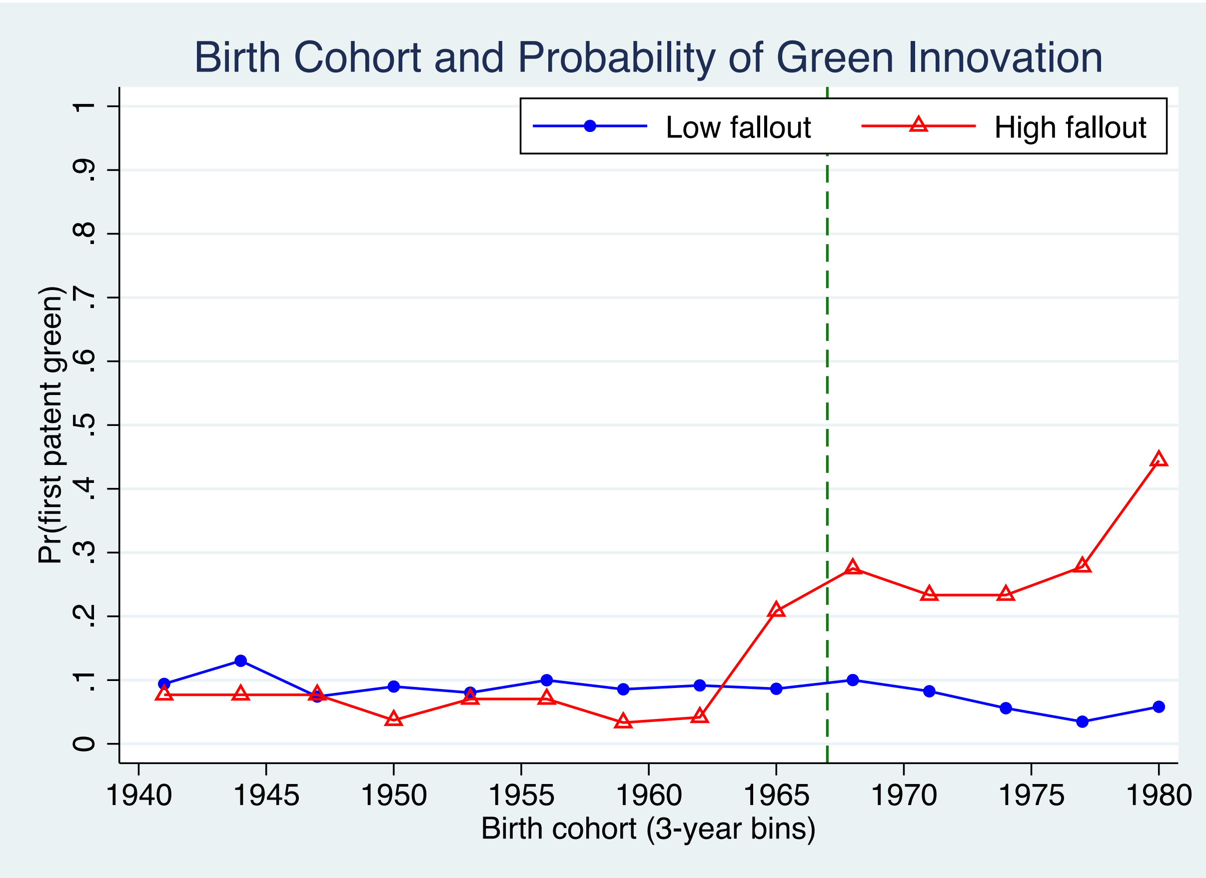


Figure A.2: The probability of the innovation being green (y-axis) by birth cohort of inventors (x-axis) and municipality fallout, where "high fallout" is defined as fallout being above the 90$^{\text{th}}$ percentile. Lines are smoothed using a centered three-cohort moving average. The cohort that was 19 years old in 1986 (born in 1967) is marked with a dashed green line.

Table A.6
Views on Environmental Investments, Nuclear Power, and Environmental Organization Activity
(Logit)

Outcome variable:	Environm. Investments (1 = Positive)		Nuclear Power (1 = Positive)		Active in env. org (1 = Yes)	
	(1)	(2)	(1)	(2)	(1)	(2)
Std. fallout	0.989*	0.983**	0.962	0.950***	0.979	0.975
	(0.007)	(0.006)	(0.026)	(0.030)	(0.024)	(0.020)
Young in 1986		1.074***		0.800***		1.199***
		(0.022)		(0.019)		(0.047)
Std. fallout × Young in 1986		1.025*		1.050		1.023
		(0.014)		(0.032)		(0.032)
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112,426	112,426	51,652	51,652	102,211	102,211
Method	Logit	Logit	Logit	Logit	Logit	Logit
Mean dep. var.	0.398	0.398	0.423	0.423	0.067	0.067

Note. Robust standard errors in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Outcome variable defined in header.

Table A.7
Views on Environmental Investments, Nuclear Power, and Environmental Organization Activity
(Controls Included)

Outcome variable:	Environm. investments (1 = Positive)	Nuclear power (1 = Positive)	Active in env. org. (1 = Yes)
Std. fallout	-0.004^{***}	-0.010	-0.001
	(0.001)	(0.007)	(0.001)
Young in 1986	0.007	-0.056^{***}	0.006^{**}
	(0.005)	(0.007)	(0.003)
Std. fallout × Young in 1986	0.005^{*}	0.014^{*}	0.000
	(0.003)	(0.007)	(0.002)
Survey wave FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	98,154	35,189	87,887
Method	LPM	LPM	LPM
Mean dep. var.	0.398	0.423	0.067
R^2	0.202	0.113	0.020

Note. Standard errors clustered at the municipality level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.8
Stickiness of Preference Shifts

Outcome variable:	Envrionm. investments (1 = Positive)	Nuclear power (1 = Positive)	Active in env. org. (1 = Yes)
Std. fallout	-0.003^{***}	-0.011^{*}	-0.001
	(0.001)	(0.007)	(0.001)
ExposedCohort	0.014^{***}	-0.050^{***}	0.011^{***}
	(0.004)	(0.005)	(0.003)
Std. fallout × ExposedCohort	0.014^{*}	0.000	0.012^{**}
	(0.008)	(0.015)	(0.005)
Std. fallout × ExposedCohort × YearsSince	0.000	0.001	-0.0004^{*}
	(0.0003)	(0.001)	(0.0002)
Survey wave FE	Yes	Yes	Yes
Observations	119,557	51,652	102,211
Method	LPM	LPM	LPM
Mean dep. var.	0.398	0.423	0.067
R^2	0.208	0.098	0.004

Note. Standard errors clustered at the municipality in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.9
Share Worried About Environmental Degradation

Outcome variable:	Share "very worried"	Share "very worried" and "somewhat worried"
Std. fallout × $I_{1987-1991}$	−0.009	0.012**
	(0.008)	(0.005)
Std. fallout × $I_{1992-1996}$	0.001	−0.002
	(0.005)	(0.003)
Std. fallout × $I_{1997-2001}$	−0.005	−0.006
	(0.006)	(0.009)
Std. fallout × $I_{2002-2006}$	−0.005	−0.003
	(0.007)	(0.002)
Std. fallout × $I_{2007-2011}$	−0.004	−0.002
	(0.005)	(0.003)
Std. fallout × $I_{2012-2016}$	0.000	0.002
	(0.005)	(0.003)
Std. fallout × $I_{2017-2021}$	0.012	−0.004
	(0.008)	(0.006)
Municipality FE	Yes	Yes
Time FE	Yes	Yes
Observations	38,761	38,761
Method	LPM	LPM
Mean dep. var.	0.489	0.893
R^2	0.008	0.004

Note. The table reports coefficients from regressions of green or total patenting per capita on fallout exposure interacted with time-period dummies. The omitted category is 1982–1986 (which consists of observations from 1986 only). All regressions include municipality and time fixed effects. Spatial standard errors are reported in parentheses. ** denotes significance at the 5% level.

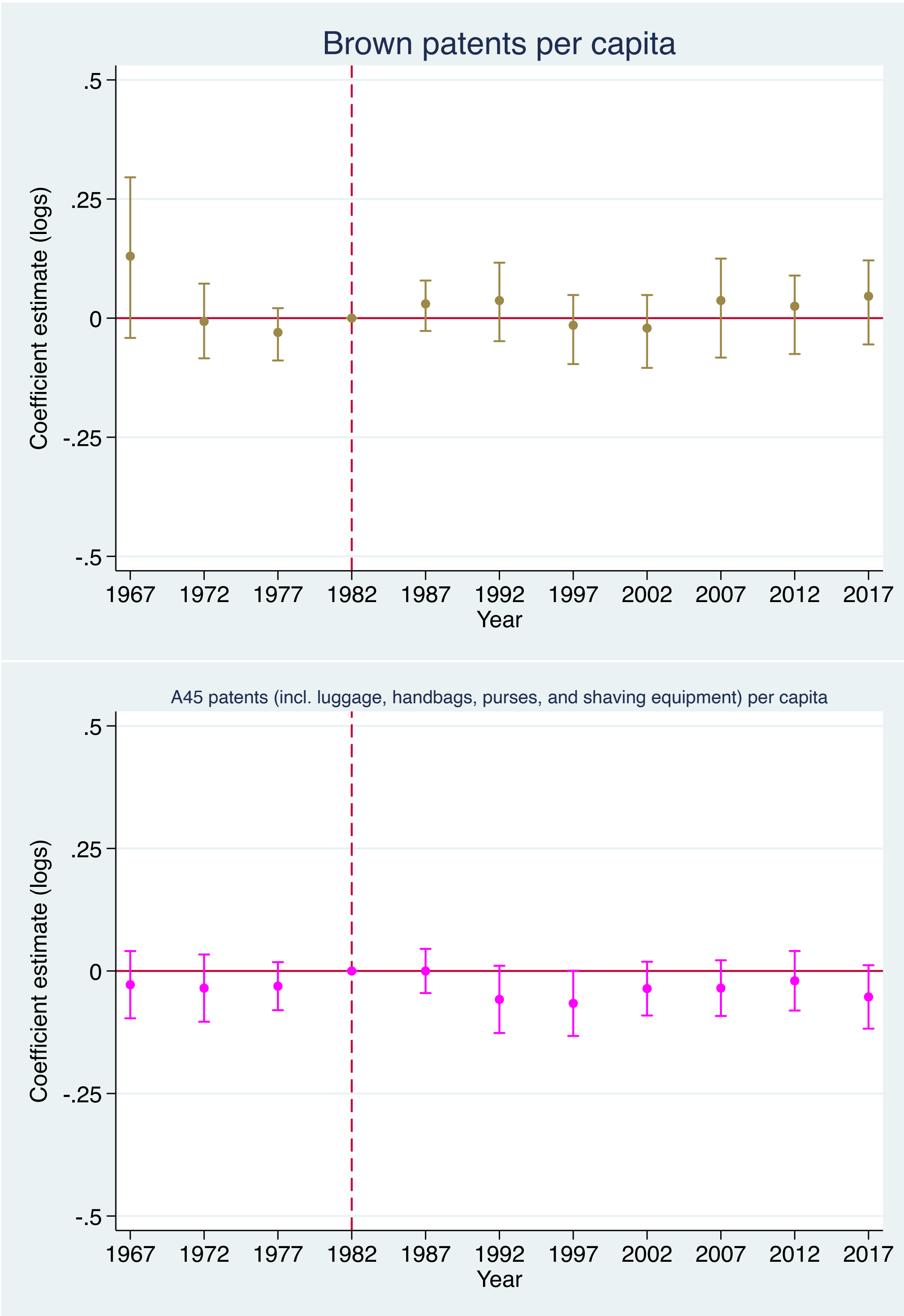


Figure A.3: Estimated Chernobyl effect on the number of brown patents per capita (top, in brown) and the A45 share (including luggage, handbags, purses, and shaving equipment) of overall patents (bottom, in pink). The pre-period, 1982–1986, is marked with a dashed vertical red line. 95% confidence intervals (CIs) derived from spatial standard errors are used.

Table A.10
Fallout Exposure and Out-Migration

	Std. out-migration, 3 years after accident (1987–1989)		Std. out-migration, 10 years after accident (1987–1996)	
	All residents	Ages 0–19	All residents	Ages 0–19
Standardized fallout exposure	−0.074*	−0.055	−0.059	−0.047
	(0.042)	(0.047)	(0.041)	(0.047)
Controls	No	No	No	No
Observations	284	284	284	284
Mean dep.var.	0.000	0.000	0.000	0.000
R^2	0.006	0.003	0.004	0.002

Note. The table reports municipality-level regressions of out-migration rates on radioactive fallout exposure from the 1986 Chernobyl accident. Columns (1) and (2) measure cumulative out-migration over the three years following the accident (1987–1989), while columns (3) and (4) measure cumulative out-migration over the ten years following the accident (1987–1996). Columns (1) and (3) include all residents, while columns (2) and (4) restrict the sample to individuals aged 0–19 in 1986. All specifications include year fixed effects and municipality-level controls. Spatial standard errors in brackets. * denotes significance at the 10% level.

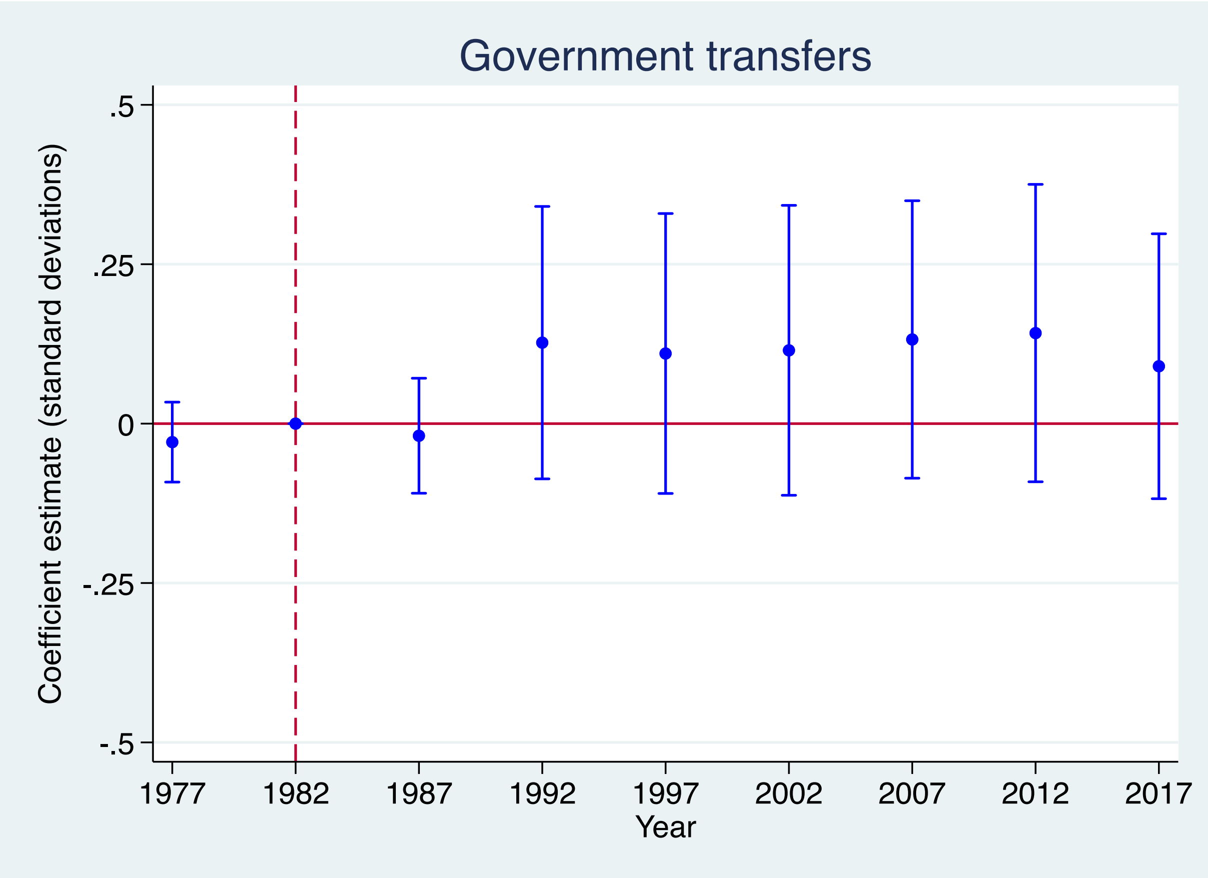


Figure A.4: Estimated Chernobyl effect on the standardized levels of government transfers per capita. The pre-period, 1982–1986, is marked with a dashed vertical red line. 95% confidence intervals (CIs) derived from spatial standard errors are used.

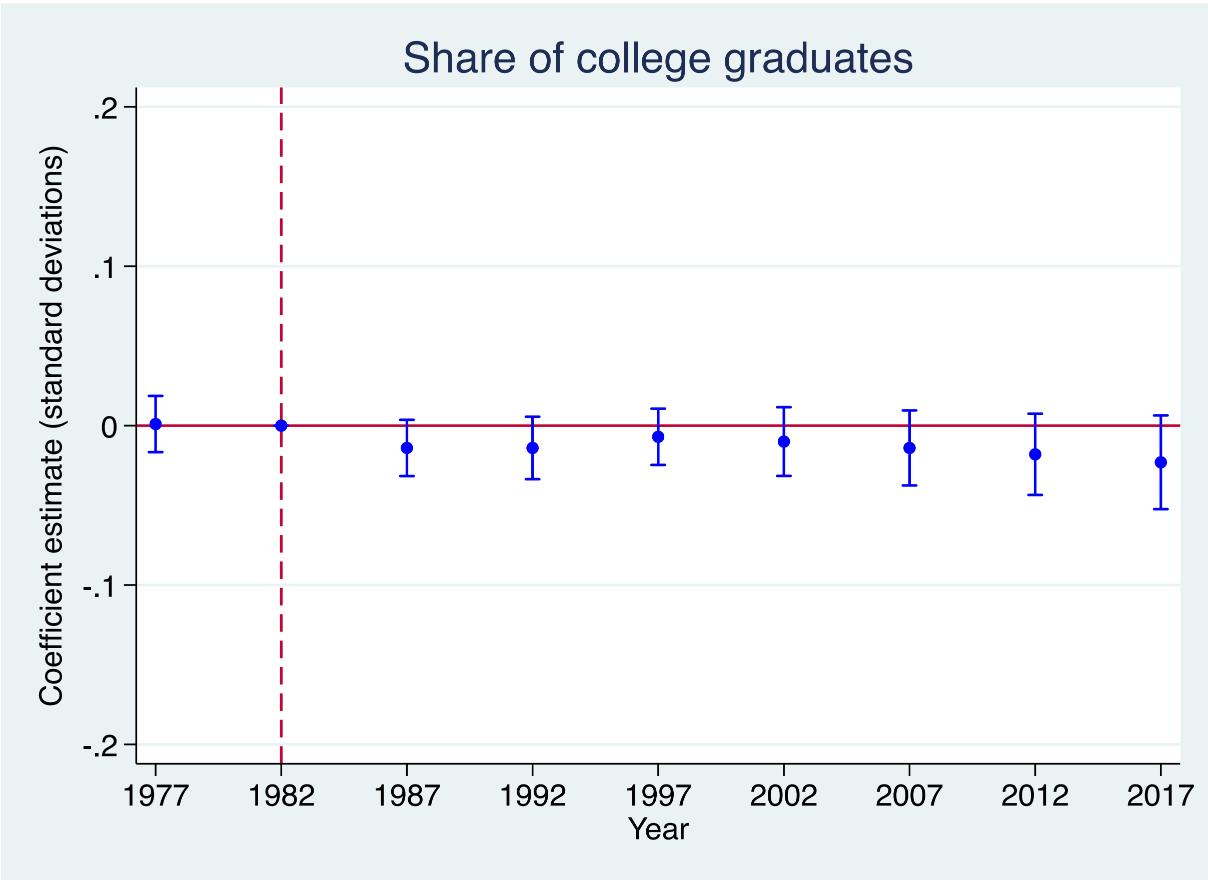


Figure A.5: Estimated Chernobyl effect on the share of college graduates including PhD's. The pre-period, 1982–1986, is marked with a dashed vertical red line. 95% confidence intervals (CIs) derived from spatial standard errors are used.

Table A.11
Fallout Exposure and Life-Course Outcomes

	Study aid	Parental benefits	Sickness leave
Std. fallout × $I_{1992–1996}$	0.005	−0.001	−0.001
	(0.007)	(0.002)	(0.014)
Std. fallout × $I_{1997–2001}$	0.012	0.0000	0.001
	(0.008)	(0.001)	(0.006)
Std. fallout × $I_{2002–2006}$	0.008	0.000	0.010
	(0.007)	(0.001)	(0.006)
Std. fallout × $I_{2007–2011}$	0.006	0.002	−0.002
	(0.005)	(0.0013)	(0.005)
Std. fallout × $I_{2012–2016}$	0.007	0.002	0.000
	(0.005)	(0.0014)	(0.0055)
Std. fallout × $I_{2017–2021}$	0.006	−0.002	−0.001
	(0.005)	(0.002)	(0.005)
Municipality FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	138,062,678	138,062,678	138,062,678
Mean dep. var.	0.000	0.000	0.000
R^2	0.350	0.212	0.100

Note. Each coefficient reports the interaction between municipality-level radioactive fallout from the Chernobyl accident and an indicator for the corresponding post-accident period. Outcomes are standardized and constructed from administrative data in LISA. All specifications include municipality and year fixed effects. Standard errors clustered by municipality. The omitted category is the 1987–1992 period.

B. Data Description

Patent data. The patent data comes from the Swedish Intellectual Property Office and covers all patent applications filed in Sweden between 1967 and 2021. The citations data comes from PATSTAT.

Data on fallout. As described in the paper, the fallout data comes from aerial measurements conducted by Swedish authorities. The variable for average ground deposition is standardized, so that the sample mean is equal to zero, and the sample standard deviation is equal to unity.

Individual-level register data. The individual-level register data is from the *LISA* database of the Swedish Statistics Agency, starting in 1990 and ending 2021. It consists of yearly observations for each individual residing in Sweden and includes data on a large number of wages, including taxable income, weeks of utilized study aid, number of days of sick leave, received pensions, parental benefits, and so on. The LISA data also includes information about the sector in which the individual works (see below for details). I restrict the sample to include only individuals aged 18–65.

Definition of green sector. To classify whether an individual works in a green sector, I use each firm's five-digit code according to the Swedish Standard Industrial Classification (SNI); this is available in LISA for each individual for each year. The following sectors are classified as green: treatment and disposal of non-hazardous waste; remediation activities and other waste management services; composting and anaerobic digestion of non-hazardous waste; deposition of non-hazardous waste; other refuse disposal; collection and treatment of sewage; collection, purification and distribution of groundwater and surface water; production, transmission and distribution of electricity; steam and hot water supply; passenger and freight rail transport; other urban and suburban passenger land transport; manufacture of electric motors, generators and transformers; manufacture of electricity distribution and control apparatus; manufacture of batteries, primary cells and accumulators; manufacture of railway locomotives and rolling stock; manufacture of industrial gases; construction and civil engineering activities and related technical consultancy; construction and other engineering activities; and research and experimental development on biotechnology, natural sciences and engineering, including interdisciplinary research and development in these fields.

Individual-level survey data. The individual-level survey data utilizes the University of Gothenburg's *SOM* database, starting in 1986 and ending 2019. This is a repeated cross-section consisting of 143,290 observations. Because questionnaires differ slightly across respondents, not all survey questions are asked of every individual.

C. Sensitivity and Power Analyses

C.A. Assessing the Parallel Trends Assumption

To examine the sensitivity of the main results to potential violation of the parallel trends assumption, I implement the Rambachan-Roth approach (Rambachan and Roth 2023; henceforth referred to as R&R), a method widely used in recent empirical studies. R&R's main robustness test involves constructing a set Δ of potential deviations from the parallel trends assumption, and then, constructing confidence intervals associated with these deviations for the parameters of interest. Using the same notation as in the paper by R&R, I denote by δ the trend, and by $M \geq 0$ the amount by which the slope of δ can change between consecutive periods. Following R&R, and using their notation $\Delta^{SD}(M)$ for the set of potential deviations (the abbreviation SD is for "second differences" or "second derivative"), we have

$$\Delta^{SD}(M) := \{\delta : |(\delta_{t+1} - \delta_t) - (\delta - \delta_{t-1})| \leq M, \forall t\} \tag{C.1}$$

In the special case when $M = 0$, the difference in trends are exactly linear. While there is nothing in the data that can place an upper bound on the value of M, it must at least be greater than or equal to the largest observed second difference in the pre-period.

In this case, the three observed pre-period point estimates for the green patent share, corresponding to the year 1967–1971, 1972–1976, and 1977–1981, are 0.078, −0.003, and 0.034, respectively. Thus, we have $M = (\beta_{-1} - \beta_{-2}) - (\beta_{-2} - \beta_{-3}) = (0.078 - (-0.003)) - (-0.003 - 0.034) = 0.118 - (-0.034) = 0.152$, which is interpreted as the maximum absolute second difference observed in the data being 0.152. To be conservative, I set $M = 0.5$, which corresponds to more than three times the magnitude of the observed pre-treatment shift.

C.B. Power Analysis for the Inventor Data

For the power analysis, I proceed as follows. Since the dependent variable is binary, I approximate the required sample size using a linear probability model. The target effect size is that a one–standard deviation increase in fallout increases the probability of green innovation by one percentage point. This corresponds to a slope coefficient of $\beta = 0.01$. The required sample size is computed for a two-sided test of $H_0 : \beta = 0$ against $H_A : \beta \neq 0$. I report required sample sizes under alternative assumptions about the correlation between fallout and the outcome variable; in this case, whether an invention is green, in the patent denoted GreenPatent. This parameterizes the residual variance of the model. To remain on the conservative side, I let the assumed correlations range between 0.10 and 0.20, while the probability of a type I error is fixed at $\alpha = 0.05$. From

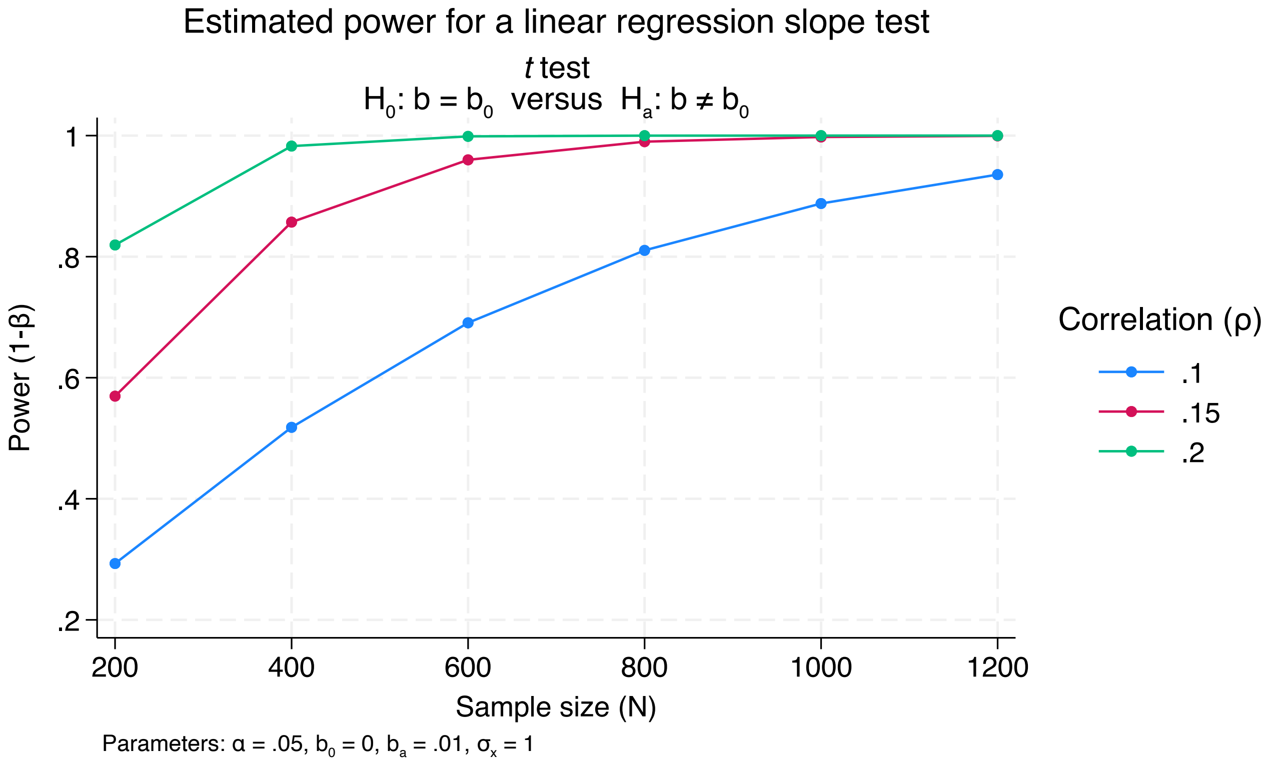


Figure A.6: Estimated power.

the above figure, we may note that even for an estimated correlation of 0.1, a sample size of around 800 is sufficient to achieve 80% power. However, since we are primarily interested in estimating the interaction coefficient $\text{Fallout}_m \times \text{Young}_{1986}$, I increase the sample size slightly, so that the final sample consists of 1,011 inventors and a total of 1,158 patents. In the end, the observed correlation between and fallout in the inventor sample was about 0.099, justifying a fairly large sample size.