Economic Meltdown? Labour Productivity and Challenges in the Aftermath of Chernobyl*

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December 27, 2024

Abstract

In 1986, an explosion occurred at the Chernobyl Nuclear Power Plant (NPP), sending an unprecedented wave of radiation across Europe—and a wave of trepidation toward other nuclear power plants across the world. We exploit this plausibly exogenous event, using gridded population data and nighttime lights data to understand how the Chernobyl disaster impacted labor productivity growth in areas close to the Chernobyl NPP (the direct effect) and areas close to non-Chernobyl NPPs (the perception effect). We have three key results. First, we find that areas closer to a non-Chernobyl NPP saw less growth in labour productivity; in other words, Chernobyl had a perception shock on labor productivity growth inversely related to distance from the nearest NPP. We demonstrate that this result is driven both by a negative effect on economic growth as well as a positive effect on population growth in cells close to non-Chernobyl NPPs. Second, in areas within 25-75km of Chernobyl, we find a positive direct effect, even after accounting for the perception effect, on labour productivity growth, driven primarily by large increase in economic activity, but also by out-migration. Finally, both the direct and perception effect diminish in size as the distance to the NPP approaches 150km. Research has long recognized, but rarely quantified, the impacts of the Chernobyl disaster, and the results of this paper provide insights into broader development challenges faced by former planned economies as well as developing and developed countries across the world, where the spectre of Chernobyl continues to shape economic trajectories today.

JEL: Q52 | O40 | J24 | J61 | R11

KEYWORDS: Chernobyl, nuclear power plant, Chernobyl disaster, renewable energy, remote sensing, labor productivity, instrumental variables, economic geography

*The authors have no conflict of interest to declare. The authors are grateful for helpful comments from Barry Reilly and Sambit Bhattacharyya.

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1 Introduction

Understanding how economies respond to large economic shocks is a crucial element in solving economic development challenges. Although this literature is wide, an area that is relatively less explored concerns nuclear shocks, the importance of which has been underscored by a recent International Atomic Energy Agency (IAEA) report predicting that nuclear capacity will double by 2050. With the production of nuclear power predicted to double by 2050, understanding the economic consequences of disasters is increasingly important.

The link between nuclear shocks and economic performance is crucial to establish policy in the event of a nuclear disaster, with the UN urging researchers to explore this relationship (UNDP, 2002). From an economic growth perspective, this is becoming increasingly important. After more than 20 years of stagnation, interest in nuclear energy was sparked in the late 2000s. Although growth is predicted in nuclear power, most of this growth is within non-OECD countries (Goldemberg, 2009). In 2017 developing countries accounted for 17% of global nuclear power generation, this is expected to increase to 40% by 2035 (Banks and Massy, 2012).

This is not too surprising given that there is a global shift in the use of clean energy and zero emissions targets. However, these goals themselves bring economic growth challenges particularly in countries which export oil and gas. Given that around half of the world's oil and gas is produced by middle-income developing countries (Saha et al., 2023), the rise in nuclear energy could have significant impacts for developing countries. However, nuclear energy brings significant risks, for example an uncontrolled reaction can have a huge geographic fall out and impact long-run economic growth through several channels including loss of human capital, destruction of infrastructure and environmental degradation and negative productivity effects. That said, the links between economic growth and nuclear disasters are unclear, and there is little existing evidence. Understanding these effects is crucial to try mitigating potential consequences in the case of any future nuclear disasters.

This paper contributes to existing research by exploring the long-term impacts of the

largest nuclear incident to-date, the 1986 Chernobyl disaster.[1] We examine the relationship between the Chernobyl disaster and long run economic growth. More specifically, we distinguish between two separate channels of impact: the direct effect of the disaster and immediate policy responses and a perception effect stemming from reluctance to locate and invest in areas proximate to the power plant. We measure these effects by utilizing a model that compares the effects on Chernobyl with those on other NPPs.

We present evidence in support of the prospects for labor productivity growth being exogenous with the distance between a nuclear power plant (NPP). We nonetheless recognize the potential for this endogenous relationship, as settlment location and NPP location is driven by a complex collection of economic, political, and geographical factors, among others. We therefore also employ instrumental variables to support the least squares results. Using multiple NPP feasibility studies, we demonstrate that public and private actors consciously consider geographic factors when choosing the location of NPP location. While it would be difficult to argue that historical rainfall and elevation are exogenous instruments with respect to labor productivity growth, we argue that settlements rainfall and elevation relative to the nearest NPP are indeed exogenous instruments and thus use them to estimate an impact similar in character to those shown by least squares. While our instrumental variables model fails traditional tests of endogeneity (like the Sargan-Hansen test), we contend that this is primarily due to our sample size of more than three-hundred thousand observations, demonstrating that we could achieve the same results by randomly dropping 90 percent of our sample and pass traditional tests of endogeneity.

We have three key results. First, we find that areas closer to a non-Chernobyl NPP saw less growth in labour productivity; in other words, Chernobyl had a perception shock on labor productivity growth inversely related to distance from the nearest NPP. Using a decomposition exercise, we demonstrate that this result is driven both by a negative effect on economic growth as well as a positive effect on population growth in cells close to non-Chernobyl NPPs. Second, in areas within 25-75km of Chernobyl, there was an positive impact on labour productivity growth. We show that this is caused primarily by large increase in economic activity in these areas, but also by migration away from these areas. Finally, the effect on labour productivity, for both the direct and

[1]On the 26th April 1986 a series of planned nuclear reactior tests led to an exploisong within the power plant, causing widespread effects

perception effect, becomes non-significant as the distance to the NPP approaches 150km.

The remainder of the paper is organised as follows. Section 2 reviews existing evidence on the long run impacts of nuclear contamination and methods for using remote sensing data as a proxy for economic growth in low-data environments. It also outlines the key details associated with the Chernobyl disaster. Section 3 describes our data sources, Section 4 outlines our empirical model for estimated the effects of the nuclear disaster on areas proximate to Chernobyl as well as areas proximate to other NPP's. It outlines our instrumental variable approach to address endogeniety concerns between NPP location and economic growth. Section 5 presents our main results, and finally we conclude in Section 6.

2 Background and Literature

On the 26th of April, 1986, an unprecedented nuclear explosion occurred in the Chernobyl Nuclear Power Plant. The explosion sent a wave of radiation across Europe, burning for ten days, with the most affected regions being Ukraine, Belarus and Russia. However, even countries as far as Sweden felt the effects. The amount of radiation released makes Chernobyl the largest nuclear disaster on record, far exceeding the levels seen in other notable nuclear incidents including Hiroshima and Nagasaki. The weeks following the accident saw a mass evacuation in the areas surrounding the plant, with the 30km immediately surrounding Chernobyl being referred to as the Chernobyl Exclusion Zone.

The mass evacuation caused the permanent reallocation of 350,000 residents, creating a wave of internal migration. This mass shift of people brought a significant change to demographics of areas they relocated too (Karácsonyi, Hanaoka, and Skryzhevska, 2020) as well as infrastructural damage, agricultural damage and mass environmental consequences. Understanding how this impacted long run economic growth is an important question, especially given that the IAEA expect global nuclear capacity to double by 2050.

The Chernobyl disaster of 1986 is telling example of how catastrophe can impact society. There is a growing literature exploring the effects of Chernobyl, including labour market effects and health effects (Lehmann and Wadsworth, 2009; Havenaar, Bromet, and Gluzman, 2016) and environmental and agriculture consequences. Yet, missing in literature is the effects nuclear disasters have on long-term economic growth (UNDP, 2002).

We aim to fill this gap by exploring the effects of Chernobyl on labour productivity in areas immediately surrounding Chernobyl, as well as any spillovers to areas surrounding other NPP's. There is some evidence documenting that Chernobyl impacted regional economic development, however much of the focus in the literature has been on the impacts of exposure to radiation, and its consequent impacts on economic outcomes.

Despite long run economic growth not directly being investigated, several findings within existing literature suggest negative effects on several outcomes that may impact growth.

Lehmann and Wadsworth (2009) exploit variation in radiation exposure and find that those more exposed have poorer health as well as significantly lower levels of labour market participation 20 years following the incident. Havenaar, Bromet, and Gluzman (2016) echo these findings, showing that areas with higher levels of radiation have poorer socio-economic outcomes, which previous research shows has a negative impact on Ukraines GDP (Lehmann and Wadsworth, 2009). They also find that in 2011 that the 600,000 people recruited to help clean up affected areas have higher rates of cancer and other conditions.

Following the disaster, agricultural productivity was significantly impacted both in areas in close proximity to Chernobyl as well as further afield. It also led to the collapse of traditional industries, particularly agriculture which was an important part of regional output. In Belarus, an estimated 1.8 million ha of agricultural land was contaminated (Durand and Bogdevitch, n.d.). In total, it is estimated that 40% of the land impacted was agricultural.

There is evidence of wider economic outcomes, including voting behaviours. Mehic (2023) finds that the Chernobyl disaster increased social resistance to nuclear energy. This suggests there may be a perception effect, where those not geographically close to Chernobyl saw changes in the way they view nuclear energy. We contribute to literature by trying to directly capture this.

3 Data

3.1 Nighttime lights and gridded population data

Night-time lights data has been shown to be a well performing proxy real growth in GDP (Henderson, Storeygard, and Weil, 2012). When choosing nighttime lights data, there are primarily two different sources of data available. The first is Defense Meteorological Satellite Program Operational Linescan System, or DMSP-OLS. Nighttime lights data sourced from DMSP-OLS were collected by older satellites, and as a result are available for earlier years but are lower resolution. The second type of nighttime lights is Visible Infrared Imaging Radiometer Suite, or VIIRS. VIIRS nighttime lights data is collected from an eponymous sensor onboard newer satellites that were launched in 2013. Consequently, VIIRS data do not have significant historical coverage, but have a higher resolution.

Because we want data as close as possible to the Chernobyl disaster, we utilize DMSP-OLS data for our analysis. There are three important issues to address when using DMSP-OLS as panel data. The first is that the the sensor on board satellites prior to 2013 was only able to detect luminosity up to a certain level. Anything above a digital number of 63 (a unit measuring luminosity) is reported as 63. This issue is known as *saturation*. The second issue is *inter-calibration*. DMSP-OLS data was collected by different satellites over time. The service dates of these satellites sometimes overlapped. In comparing these data over time, we know that slight differences exist in the data collected by the sensors on the different satellites. These idiosyncrasies require inter-calibration in order to properly compare luminosity across time. The final issues is *blooming*, when atmospheric scattering or light sensor overexposure leads to areas of concentrated light bleeding into nearby areas.

Zhao et al. (2022) provide a full panel of DMSP-OLS nighttime lights data from 1992 to 2013 that correct for these issues. 1992 is the first year that the DMSP-OLS data were made available, and these data were discontinued after 2013, so Zhao et al. (2022) offer corrected-data for the full period of availability of DMSP-OLS. Throughout this paper, the mention of nighttime lights, except when otherwise noted, refers to corrected DMSP-OLS data sourced from Zhao et al. (2022).

We source spatial population data from Global Human Settlement Layer (GHSL), which applies models to data inputs, including satellite images of built-up area, household surveys, and others, to estimate the population living at a given location across the world. We aggregate (sum) both nighttime lights data and gridded population data into cells of length $3.5km$ ($12.25km^2$). Following studies that use similar data (e.g. (Jha et al., 2024)), we calculate nighttime lights per capita and use it as a key outcome of interest. One practical difficulty for calculating nighttime lights per capita is that GHSL data is only available every five years coinciding with the start and middle of each decade. In response, we create 1992 nighttime lights per capita using 1992 nighttime lights data and 1990 population data; to create 2013 nighttime lights per capita, we use nighttime lights data from 2013 and poulation from 2015. Except where otherwise noted, we exclude from our sample observations that had zero or missing values of nighttime lights per capita in either 1992 or 2013.

We have some doubts about the reliability of population data in the Chernobyl exclusion zone. According to GHSL data, population within 10km of Chernobyl increased from 11,809 to 12,499 from 1985 to 1990. We know that due to evacuations, this cannot be accurate. The Chernobyl disaster highlight the limitations of GHSL data, as key inputs like built up area had not changed much over this time and (to the authors' awareness) no significant household survey had been completed that could inform estimates. For this reason, we proceed with caution when interpreting nighttime lights data within the exclusion zone.

3.2 Geographic data

This paper draws on a rich source of geographic data that stem from a variety of sources. It utilizes land use data from Copernicus Land Monitoring Service. It takes historical climate variables such as temperature, minimum temperature, maximum temperature, seasonality, and rainfall from Hijmans et al. (2005).Elevation and ruggedness come from the United States Geological Survey (USGS).

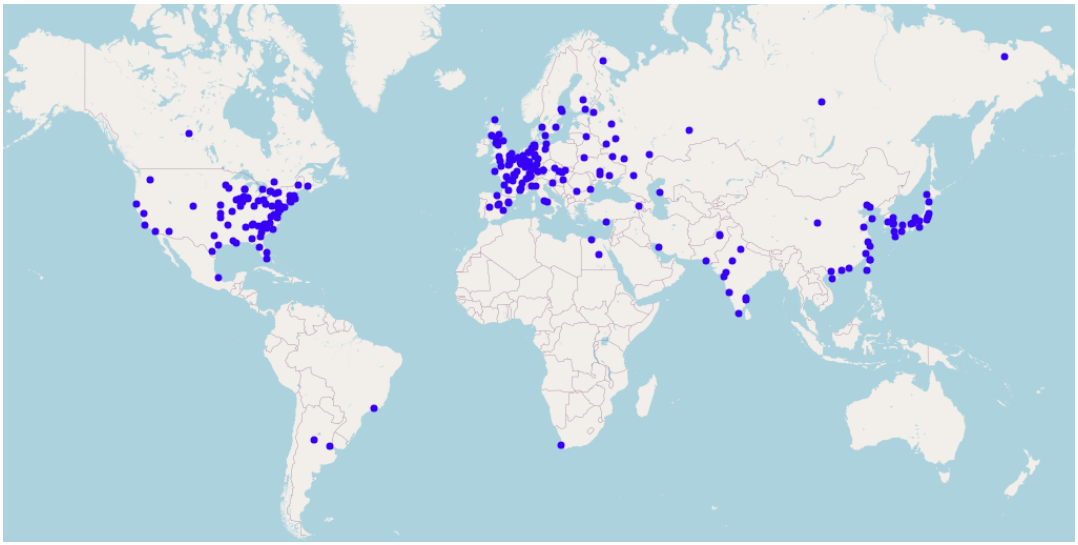
It is important to articulate exactly how these data are aggregated. Take elevation and ruggedness, for example. The data are first captured at a very fine resolution and then aggregated into coarser cells to make their storage and use more practical. In going from fine to course, information is lost. In the case of elevation, the values from very

small cells is averaged to produce the value for the larger cell. In the case of ruggedness, the larger cell represents the standard deviation of the finer cells multiplied by 100.[2] In our analysis, we aggregate this information a second time. When we aggregate this data into larger $3.5km$ cells, we also lose some information. For nighttime lights and population, we sum this information across smaller cells to form larger ones. For elevation, ruggedness, measures of temperature, and rainfall, we average this information. In practice, the importance of this step does not extend far beyond interpretation of results.

3.3 Nuclear Power Plant Data

Using data from the International Atomic Energy Agency (IAEA), we have the name, country, as well as several other characteristics including the time of construction, for NPPS across the globe. Utilizing Python's Google Maps package, we are able to precisely located the NPPs in the IAEA data. Figure 1 presents the spatial distribution of NPP's in the sample. NPP's tend to be located in Europe and North America, both having a sizeable cluster of NPP's. A small but non-negligible share of our data have multiple NPPs within 250km. In the case of a cell having multiple NPPs nearby, we record the distance of the closest NPP. Distance is measured from the NPP coordinates to the centroid of a given cell.

Figure 1: Geographic distribution of NPPs sampled



[2]More details about this process are provided by USGS on page 8 of this report.

4 Empirical specification

4.1 Identifying two channels for impact

There are two important channels through which the Chernobyl disaster could affect economic growth in the long run. The first channel, which we call the *direct effect*, is the direct impact of the disaster. Nuclear radiation causes negative health outcomes, which reduces labor productivity. Forced migration causes large demographic swings, which could affect labor productivity positively or negatively. It is important to note that the direct effect, therefore, is not purely an estimate of the effect of radiation. The second channel, or what we call the *perception effect*, is a public response to the risk posed by radiation. Various actors in society—households, companies, and governments—all invest less in areas proximate to NPPs due to the risk posed by radiation.

Our dataset provides detailed information about the characteristics and growth of areas surrounding both Chernobyl and other NPPs that were in operation at the time of the Chernobyl disaster. We capitalize on this coverage to try to disentangle these two channels of impact. There is not a perfect way to do this. We start by assuming that proximity to non-Chernobyl NPPs in the aftermath of the Chernobyl disaster represents the perception effect. In practice, this serves as a lower-bound for the perception effect, since for these NPPs there was not an imminent threat posed by contamination. By integrating these data with data on areas proximate to Chernobyl to estimate a direct effect of the disaster in addition to the perception effect.

Because we want to allow the possibility of nonlinear effects with respect to disastance from an NPP, our preferred specification utilizes a vector of binary variables that indicate distance. It is not immediately obvious, however, how many rings to include in the specification, so we calculate the Baysian information criteria for a nested model with increasingly fewer rings in order to determine the appropriate number of rings. Due to sample size constraints, we test rings as small as 25km, which is also conveniently the average size of the exclusion zone. Our initial specification is thus:

$$\begin{aligned}\tilde{y}_{ip,1992-2013} = \beta_0 + \sum_{r\in\mathcal{R}} \beta_1^r t_p * D_{ip}^r + \beta_2^r D_{ip}^r \\ +\alpha_0 t_p + \boldsymbol{\lambda X_{ip}} + \epsilon_{ip}\end{aligned} \tag{1}$$

where $\tilde{y}_{ip,1992-2013}$ is the growth in nighttime lights (DMSP-OLS) in cell i near nuclear power plant p from 1992 to 2013, t_p is a dummy variable for Chernobyl, and D_{ip}^r is a dummy for being in a band between radius r and $r - 25km$ away from the NPP, $\boldsymbol{X_{ip}}$ is a vector of controls, including population density in 1990, nighttime lights per capita in 1992, total nighttime lights in 1992, country fixed effects, and NPP characteristics like plant type and generating capacity. The coefficient β_1^r estimates the direct effect of the Chernobyl disaster on being located in ring r (for those cells nearby Chernobyl), while β_2^r estimates the perception effect of being located in ring r (for all cells). Table 1 contains the BIC for different nested models, each with a different number of rings. We select the model with the smallest BIC, which is the model with six rings. This implies, when interpreting the results from Equation 1 that the area 150km to 250km away from a given NPP serves as the *de facto* comparison group.

Table 1: Information criteria used to select the number of treatment bands

Radius	# of rings	N	AIC	BIC	Adjusted R2	AIC Rank	BIC Rank	Adj R2 Rank	Avg Rank
25	6	7,860	27,357	27,413	0.020	5	1	5	3.7
25	7	7,860	27,350	27,413	0.021	4	2	4	3.3
25	10	7,860	27,343	27,419	0.022	2	4	1	2.3
25	9	7,860	27,343	27,419	0.022	1	3	2	2.0
25	8	7,860	27,350	27,419	0.021	3	5	3	3.7
25	5	7,860	27,374	27,423	0.018	6	6	6	6.0
25	4	7,860	27,394	27,436	0.015	7	7	7	7.0
25	3	7,860	27,447	27,482	0.008	8	8	8	8.0
25	2	7,860	27,476	27,504	0.004	9	9	9	9.0
25	1	7,860	27,507	27,528	0.000	10	10	10	10.0

4.2 Endogeneity of location

If settlements could be randomly placed, NPPs themselves randomly scattered across habitable areas, the Chernobyl shock could be entirely exogenous. The issue is that far from random, both settlments and NPPs are the product of careful throught out actions from both actors based on geographical factors, political factors, and economic factors. The resulting issue, therefore, is that the distance of a settlement relative to the NPP could be endogenous.

Because we do not have data prior to 1986, we cannot rely on a difference-in-difference specification to estimate causal impacts. Applying regression discontinuity design to the exclusion zone represents an attractive alternative. However, given that the exclusion zone was almost entirely depopulated, the results are both difficult to interpret and

are plagued with tricky measurement errors (to the authors' knowledge, no large-scale household surveys have been carried out in the exclusion zone since the disaster).

To effectively use instrumental variables, we need to find an instrument that explains the location of settlements relative to the closest NPP. There are limitations on the economic and political data that could be informative of distance to the nearest NPP. For this reason, we focused our attention on geographical variables that could serve as a valid instrument. The dual challenge, of course, is that this instrument also must be uncorrelated with the outcome of interest (growth in NTL per capita) except through the endogenous variable (distance to the closest NPP).

To overcome this endogeniety concern, we instrument distance to an NPP using relative elevation. That is, we measure the relative elevation of a given cell in comparison to the elevation of cell containing the nearest NPP. NPPs are typically placed in geographic areas with an elevation that can mitigate effects of weather shocks (e.g. flooding), and assist in the cooling of the NPP (Enercon Services, 2024). In practice, as noted in numerous NPP feasibility studies, this is located close to but above water sources, but that are low in elevation relative to the surrounding area, meaning NPP sites tend to be local minimums with respect to elevation. For robustness we use a second instrument of relative historical[3] rainfall. NPP feasibility studies highlight the desirability of stable temperatures without extreme amounts of rainfall. In practice, NPP locations tend to be local maximums of rainfall. In our data, relative rainfall has a negative relationship with distance from the nearest NPP, while relative elevation has a positive relationship.

It would be difficult to argue that historical rainfall and elevation are instruments that are exogenous with labor productivity growth. Deserts, for example, are generally inhospitable climates to build cities. Moreover, humans need oxygen to thrive, and areas of high elevation do not have as high of concentrations of oxygen in the air. In fact, there is not a city in a developed country of at least a million people located at an elevation higher than 7,500 feet (World Economic Forum). While historical rainfall and elevation may be correlated with prospects for labor productivity growth and simultaneously are factors of NPP location, NPPs are not typically built in areas of extreme geography, such as in rain forests or the Himalayas. For this reason, we argue that both relative elevation and rainfall are unlikely to influence economic growth and are thus exogenous

[3]We use average annual rainfall data from 1960 to 1991).

instruments. Because we only have two instruments, estimating Equation 1 would lead to underspecification. For this reason, we adapt Equation 1 by allowing for effects to be linear in distance and run this specification separately for cells near Chernobyl and those near other NPPs. The specification is thus

$$\textbf{First stage: } Dist_{ip} = \gamma_0 + \gamma_1 RelElevation_{ip} + \gamma_1 RelRainfall_{ip} + \boldsymbol{\gamma_3 X_{ip}} \tag{2}$$

$$\textbf{Second stage: } \tilde{y}_{ip,1992-2013} = \alpha_0 + \alpha_1 \hat{Dist}_{ip} + \boldsymbol{\alpha_2 X_{ip}} + \epsilon_{ip} \tag{3}$$

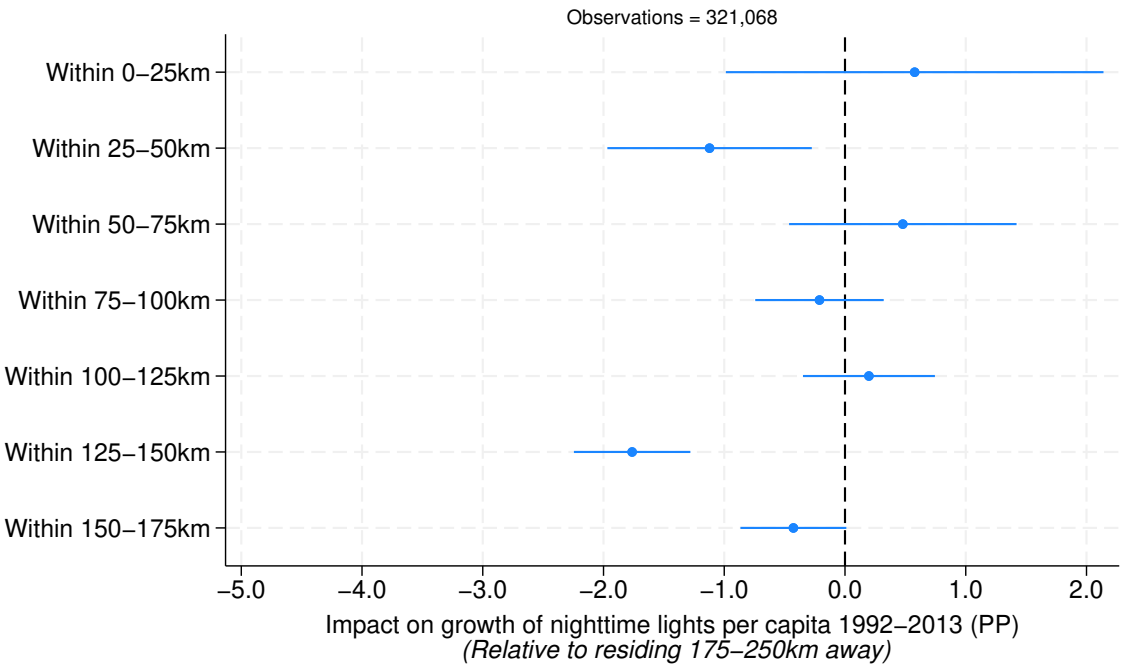
where D^r_{ip} is the distance to the nearest NPP, $\tilde{y}_{ip,1992-2013}$ is the predicted value of distance from the first stage, RelElevation and RelRainfall are our instruments, and $\boldsymbol{X_{ip}}$ is our vector of controls, containing the same covariates as in Equation 1 Our sample of cells consist of those up to 150km away from the nearest NPP. We do this so that our results are consistent with Equation 1, and because it is difficult to compare the BIC of non-nested models.

5 Results

5.1 Pretrends and Exogeneity

One way to assess Equation 1 for omitted variable bias is by estimating the specification only for those NPPs whose construction started after 1986. These include NPPs that were planned, financed, and built, but also those that were not even planned until after 2013. Figure 2 displays the results of this specification. As can be seen, there does not appear to be any consistent statistically-significant and economically-meaningful association between being located near an NPP build post-1986, relative to being 150-250km away from one.

Figure 2: Percentage point change in nighttime lights per capita 1992-2013: NPPs constructed after 1986, excluding Chernobyl



Note: The figure is created using estimates from Equation 1 with robust standard errors. Nighttime lights per capita utilizes DMSP-OLS data that are adjusted for issues of inter-calibration, blooming, and saturation. Population data come from the Global Human Settlement Layer. The The sample contains only cells whose closest NPP's construction began after the Chernobyl disaster in 1986. The control variables include population density in 1990, nighttime lights per capita in 1992, sum of nighttime lights in 1992, country fixed effects, land use fixed effects, reactor characteristics, elevation, ruggedness, maximum annual temperature, minimum annual temperature, and rainfall. Cells that had zero or missing nighttime lights per capita in 1992 or 2013 are not included in any of the regressions. Error bars show 95% confidence interval.

5.2 Main Results

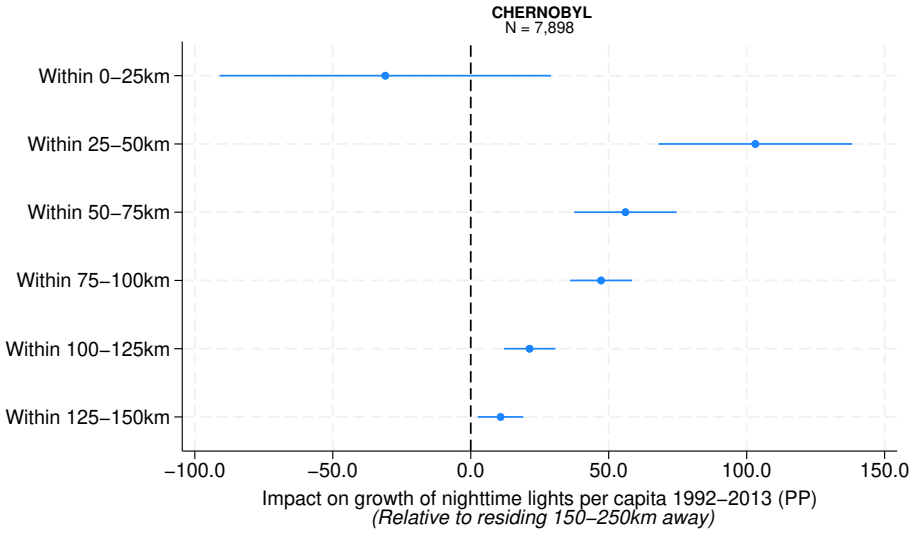
Figure 3a and Figure 3a present the results for Equation 1, running it separately for Chernobyl and non-Chernobyl NPPs. The results show that, compared to a baseline of settlements 150-250km away from the nearest NPP, there is a dampening effect on labor productivity growth the closer a settlement is to a NPP. This effect is lowest for settlements in the ring closest to a NPP (0-25km) and approaches zero somewhat linearly as distance increases. We cannot rule out a null effect for settlements within 25km of Chernobyl. As noted earlier, measurement error and noise make it difficult to make conclusions about the impact in this area. The wide error bars on the 0-25km coefficient likely reflect, to some degree, the wide array of experiences of settlements in this area, which had mostly been depopulated, with some re-population during our study period. Interestingly, the second ring from Chernobyl (25-50km) experienced a positive impact on labor productivity growth. We hypothesize that this stems from an increased internal migration combined with investments from the Soviet Union, and later Ukraine and Belarus, to re-plan essential infrastructure in this area. In general, outside of the first ring, the impact of the Chernobyl disaster on areas next to Chernobyl has a positive effect on per capita growth that diminishes over distance, mirroring that seen in non-Chernobyl NPPs.[4] For both Chernobyl and non-Chernobyl plants—or in other words, both the direct effect and perception effect—impact on growth per capita dies out by the 150km mark, consistent with what the BIC indicated in Table 1.

Table 2 presents the results for the specification in Equation 3. The results in the OLS column are from Equation 3, except that the use actual rather than predicted data for distance and it includes Chernobyl-distance interaction term to separately measure the direct effect and perception effect. With a sample size of several hundred thousand observations, common tests of heteroskedasticity, whose test statistics increase linearly with sample size, will almost always reject the null of homoskedasticity. While therefore difficult to test formally, we believe that there is likely heteroskedasticity present for multiple variables in our model. As a result we also run Equation 3 with robust standard errors. Because the GMM estimator is more efficient than the IV estimator in the presense of heteroskedasticity, we estimate the equation using GMM (Baum, Schaffer, and Stillman, 2003).[5] Finally, as noted in the previous section, we do not include an inter-

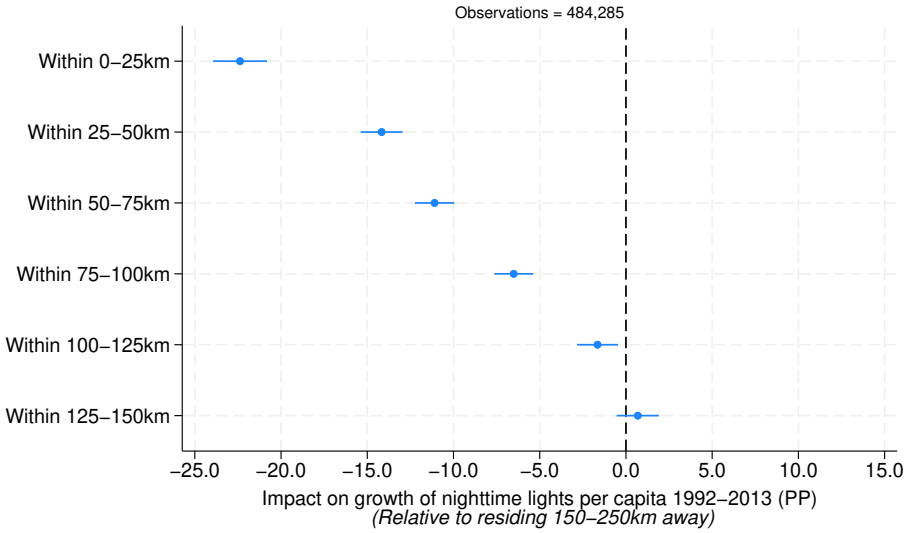
[4]For interpretation purposes, Kyiv is located almost entirely within the 100-125km ring.

[5]It can be shown that the GMM point estimate is the same as the IV point estimate when conditional homoskedasticity is assumed, or when the model is exactly identified. This is readily seen in Table 2.

(a) Percentage point change in nighttime lights per capita 1992-2013: Chernobyl only



(b) Percentage point change in nighttime lights per capita 1992-2013: NPPs constructed prior to 1986, excluding Chernobyl



Note: The figure is created using estimates from Equation 1 with robust standard errors. Nighttime lights per capita utilizes DMSP-OLS data that are adjusted for issues of inter-calibration, blooming, and saturation. Population data come from the Global Human Settlement Layer. The Chernobyl sample contains only observations for which the closest NPP is Chernobyl. The control variables include population density in 1990, nighttime lights per capita in 1992, sum of nighttime lights in 1992, country fixed effects, land use fixed effects, reactor characteristics, elevation, ruggedness, maximum annual temperature, minimum annual temperature, and rainfall. Cells that had zero or missing nighttime lights per capita in 1992 or 2013 are not included in any of the regressions. Error bars show 95% confidence interval.

action term for the IV/GMM estimates because it would result in under-identification. As a result, we are not able to distinguish between the perception and direct effects in the IV/GMM specifications. Estimates involving the "Other NPPs" sample capture the direct effect, but those involving only Chernobyl capture both effects simultaneously.

The results reveal a negative, statistically significant effect of the Chernobyl disaster on proximity to non-Chernobyl NPPs (in other words, the closer a settlement is, the weaker the per capita growth). These results are not sensitive to the estimation method used (OLS, IV, or GMM) or the instrument used (relative elevation or relative rainfall), although it is worth noting that tests of validity for the relative rainfall instrument only marginally clear the threshold of 10. Under the OLS column, β_1 reflects the perception effect of the Chernobyl disaster, β_2 captures the direct effect, and their sum conveys the total effect for those settlements near the Chernobyl NPP. In terms of the perception effect, for every 1km farther away from a non-Chernobyl NPP, cells experienced 0.186 percentage points stronger growth. The direct effect goes in the opposite direction. For every 1km farther away from the Chernobyl NPP, cells experienced 1.145 percentage points weaker growth. From Figure 3a, we may surmise that this large coefficient is largely driven by the area just outside of the Chernobyl exclusion zone, whose per capita nighttime lights grew relatively rapidly from 1992 to 2013.

The direction and magnitude of the IV/GMM estimates are generally similar to those from OLS. The coefficients measuring the perception effect are all positive and significant, while the coefficient measuring the summed effect on observations close to Chernobyl is negative and significant. The primary difference between the OLS and IV/GMM results is the coefficient on relative rainfall, which is rather large—too large, in fact, to make economic sense. For this reason, combined with the fact that the F statistic indicates only marginal relevance, we prefer to place more emphasis on the results that utilize the relative elevation instrument.

That said, the standard errors need not be the same and it can be shown that the standard errors will associated with the GMM estimator will less than or equal to the IV estimator in these cases.

Table 2: Impacts of proximity to NPP following Chernobyl disaster: OLS, IV, and GMM

Dependent variable:	**OLS**	**Instrumental variables**				**GMM**			
Log growth in NTL per capita		*Z = Relative Elevation*	*Z = Relative Rainfall*	*Z = Both instruments*	*Z = Both instruments*	*Z = Relative Elevation*	*Z = Relative Rainfall*	*Z = Both instruments*	*Z = Both instruments*
(β_1) Distance to nearest NPP	**0.186**	**0.694**	**8.997**	**1.200**		**0.694**	**8.997**	**1.059**	
	(0.006)* **	**(0.280)*** **	**(2.789)*** **	**(0.249)*** **		**(0.269)*** **	**(2.783)*** **	**(0.267)*** **	
(β_2) Distance X Chernobyl	**-1.145**				**-2.254**				**-1.902**
	(0.147)* **				**(0.232)*** **				**(0.214)*** **
$\beta_1 + \beta_2$	**-0.960**								
	(0.147)* **								
Sample	All	Other NPPs	Other NPPs	Other NPPs	Only Chernobyl	Other NPPs	Other NPPs	Other NPPs	Only Chernobyl
Obs	308,973	307,188	307,188	307,188	1,785	307,188	307,188	307,188	1,785
Validity (F-Stat):		134.9***	11.3***	70.7***	478.5***	135.0***	11.3***	71.5***	478.5***
Sargan/Hansen test statistic				67.7***	58.5***			53.4***	63.5***
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors	Robust	Standard	Standard	Standard	Standard	Robust	Robust	Robust	Robust

Notes: Nighttime lights per capita utilizes DMSP-OLS data that are adjusted for issues of inter-calibration, blooming, and saturation. Population data come from the Global Human Settlement Layer. The OLS results are calculated by estimating Equation 3 except with two departures: 1) it includes an interaction term with Chernobyl and distance, and 2) it utilizes the actual values of distance instead of the those predicted from the first stage equation. The IV and GMM results are calculated by running Equation 2 and Equation 3. The Chernobyl sample contains only observations for which the closest NPP is Chernobyl. The control variables include population density in 1990, nighttime lights per capita in 1992, sum of nighttime lights in 1992, country fixed effects, land use fixed effects, reactor characteristics, elevation, ruggedness, maximum annual temperature, minimum annual temperature, and rainfall. Cells that had zero or missing nighttime lights per capita in 1992 or 2013 are not included in any of the regressions. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Testing for endogeneity

Table 2 also shows that various IV specifications fail the Sargan-Hansen test. We think there are two plausible reasons this is the case. The first is that the model is misspecified because the exclusion restriction does not hold. The second is that common tests are not optimal for large dimensional datasets. As exemplified by Equation 4 ($\hat{u}$ are IV residuals, P_z is the IV projection matrix, and n is sample size), common test statistics of instrument orthogonality increase linearly with sample size, meaning that in large samples such as ours, even minute, economically meaningless differences could result in a rejection of the null hypothesis of the Sargan test, which is that all instruments are orthogonal to the error term.

$$Sargan's\ statistic = \frac{\hat{u}' P_z \hat{u}}{\hat{u}'\hat{u}} n \tag{4}$$

The relationship between the Sargan-Hansen statistic and sample size is easily seen by bootstrapping increasingly larger subsamples of the data and then re-estimating Equation 3 with both instruments and testing again for instrument endogeneity. The results of this exercise can be found in Table 3, which shows average values from 50 resamples with replacement for each row. Column 1 and 2 show the share of the sample

bootstrapped and the sample size respectively. Column 5 shows that the coefficient estimate appears to be unbiased and consistent (assuming these characteristics are both true of the same estimate in Table 2). With only around 10 percent of our sample size, we already achieve the same results observed in Table 2 with greater than 95 percent confidence. By contrast, we don't achieve irreversible evidence of endogeneity until the sample reaches almost 100,000, roughly one-third of our entire sample. This exercise underscores the interesting fact that, statistically speaking, we could drop 90 percent of our sample and achieve the same conclusions but without an endogeneity problem.

Table 3: Testing for endoeneity by bootstrapping sample

Number of re-draws	(1) Share of observations sampled (%)	(2) Sampled observations	(3) Sargan-Hansen Statistic	(4) Sargan-Hansen p-value	(5) Coefficient	(6) Coefficient p-value
50	4	12,359	2.29	0.388	1.089	0.154
50	8	24,718	4.17	0.229	0.999	0.057
50	12	37,077	5.92	0.170	0.943	0.029
50	16	49,436	5.47	0.153	1.032	0.007
50	20	61,795	8.72	0.029	0.948	0.003
50	24	74,154	8.63	0.033	0.975	0.000
50	28	86,512	8.97	0.062	0.991	0.000
50	32	98,871	10.78	0.021	0.988	0.000
50	36	111,230	14.64	0.020	1.004	0.000
50	40	123,589	14.62	0.017	1.006	0.000
50	44	135,948	15.29	0.003	0.994	0.000
50	48	148,307	17.07	0.003	1.036	0.000

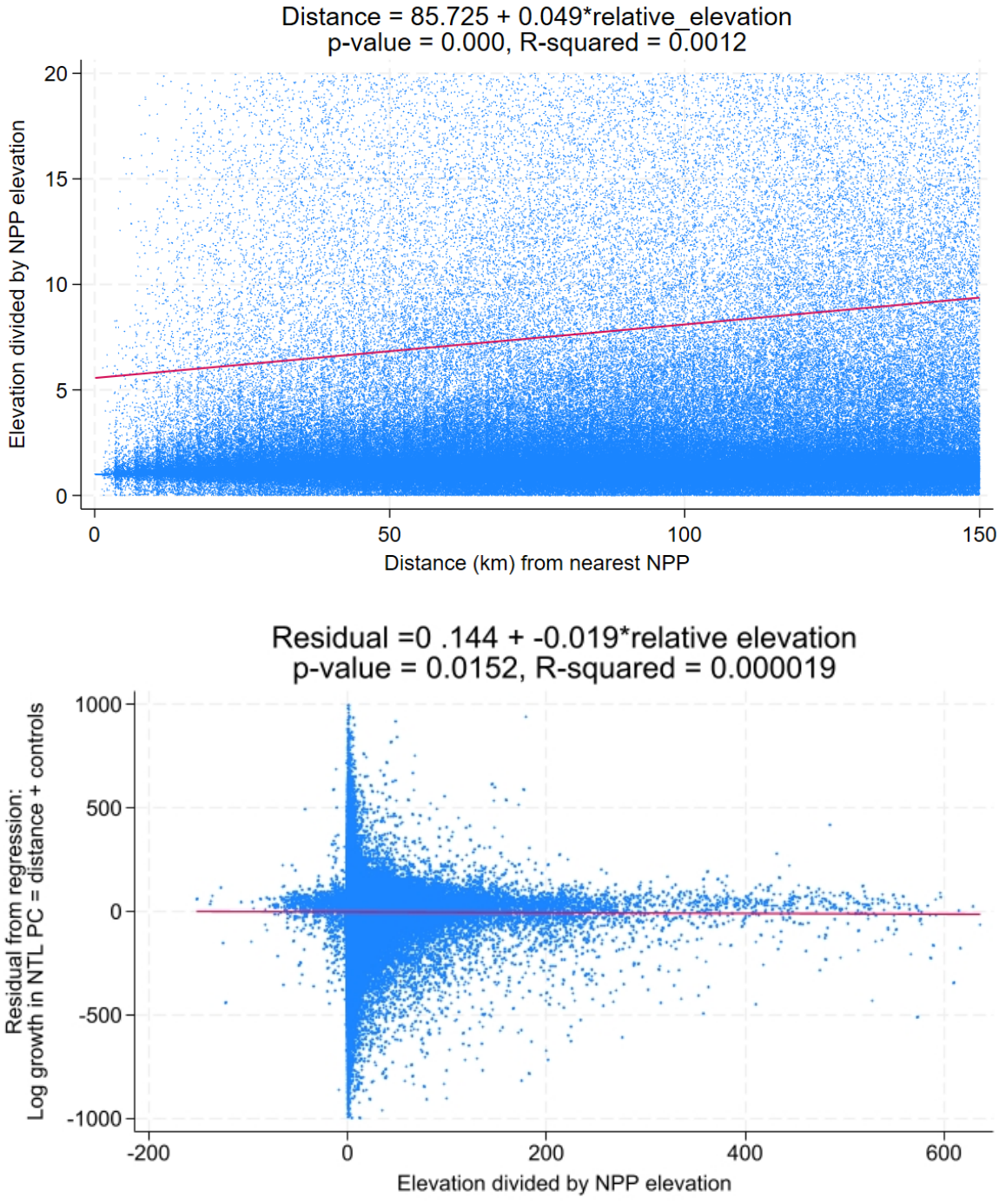
Notes: Columns 5 and 6 are calculated by running Equation 3 on the subsamples. Columns (3) and (4) are derived from these results.

Figure 4 shows another way to look at the relationship between the Sargan test-statistic and sample size. Regressing distance from the nearest NPP on relative elevation, produces a coefficient p-value of $1.0e^{-}85$. In fact, it explains about 0.12 percent of all the variation settlement distance from the nearest NPP. Given the many historical and economic features that affect location, we judge this as a non-negligible share. In contrast, relative elevation explains less than 0.002 percent of the residuals stemming from Equation 1 (second graph of Figure 4). The associated p-value of the regression of these

residuals on the relative elevation instrument is 0.015. It is statistically significant, even though relative elevation explains so little of its variation. But with more than 300,000 observations, how could it not be?

But more importantly, is the significant coefficient of -0.019 economically significant? In our sample, the 90th percentile of relative elevation is 13, meaning 13 times higher elevation than the elevation of the nuclear power plant. The data implies that residing at an elevation 13 times higher than the nearest NPP will result in 0.23 percentage points slower growth from 1992 to 2013 than residing at the same elevation as the nearest NPP. This figure is tiny in comparison to our OLS, IV, and GMM estimates in Table 2 and tiny in comparison to the average and median growth in nighttime lights per capita (58 and 35 percentage points respectively). Finally, 0.23 percentage points of growth over a 21 year period would not be considered large by any careful observer of economic history. A similar story plays out with relative rainfall. For these reasons, we believe that the IV and GMM results presented in this section complement those derived from OLS and are able to provide some indication of the causal impact of the Chernobyl disaster on productivity growth.

Figure 4: Validity and exogeneity of the relative elevation instrument



5.4 Growth decomposition

The numbers presented in Table 2 and especially in Figure 3a and Figure 3b raise questions about what exactly is driving the results. To shed light on these dynamics, we derive an estimator that can separately measure effects on growth of nighttime lights and effects on growth of population.

$$ln(\frac{y_{2013}}{y_{1992}}) = ln(y_{2013}) - ln(y_{1992}) \tag{5}$$

$$\iff ln(\frac{y_{2013}}{y_{1992}}) = ln(\frac{Y_{2013}}{L_{2013}}) - ln(\frac{Y_{1992}}{L_{2991}}) \tag{6}$$

$$\iff ln(\frac{y_{2013}}{y_{1992}}) = (ln(Y_{2013}) - ln(L_{2013})) - (ln(Y_{1992}) - ln(L_{1992})) \tag{7}$$

$$\iff ln(\frac{y_{2013}}{y_{1992}}) = ln(Y_{2013}) - ln(L_{2013}) - ln(Y_{1992}) + ln(L_{1992}) \tag{8}$$

$$\iff ln(\frac{y_{2013}}{y_{1992}}) = ln(Y_{2013}) - ln(Y_{1992}) + ln(L_{1992}) - ln(L_{2013}) \tag{9}$$

$$\iff ln(\frac{y_{2013}}{y_{1992}}) = ln(Y_{2013}) - ln(Y_{1992}) - (ln(L_{2013}) - ln(L_{1992})) \tag{10}$$

$$\iff \underbrace{ln(\frac{y_{2013}}{y_{1992}})}_{\textbf{Growth in NTL PC}} = \underbrace{ln(\frac{Y_{2013}}{Y_{1992}})}_{\textbf{Growth in NTL}} - \underbrace{ln(\frac{L_{2013}}{L_{1992}})}_{\textbf{Growth in population}} \tag{11}$$

It can be shown the optimal estimator for Equation 1 is $(X'X)^{-1}X'\tilde{y}$. Plugging Equation 11 into the equation for the optimal estimator, gives

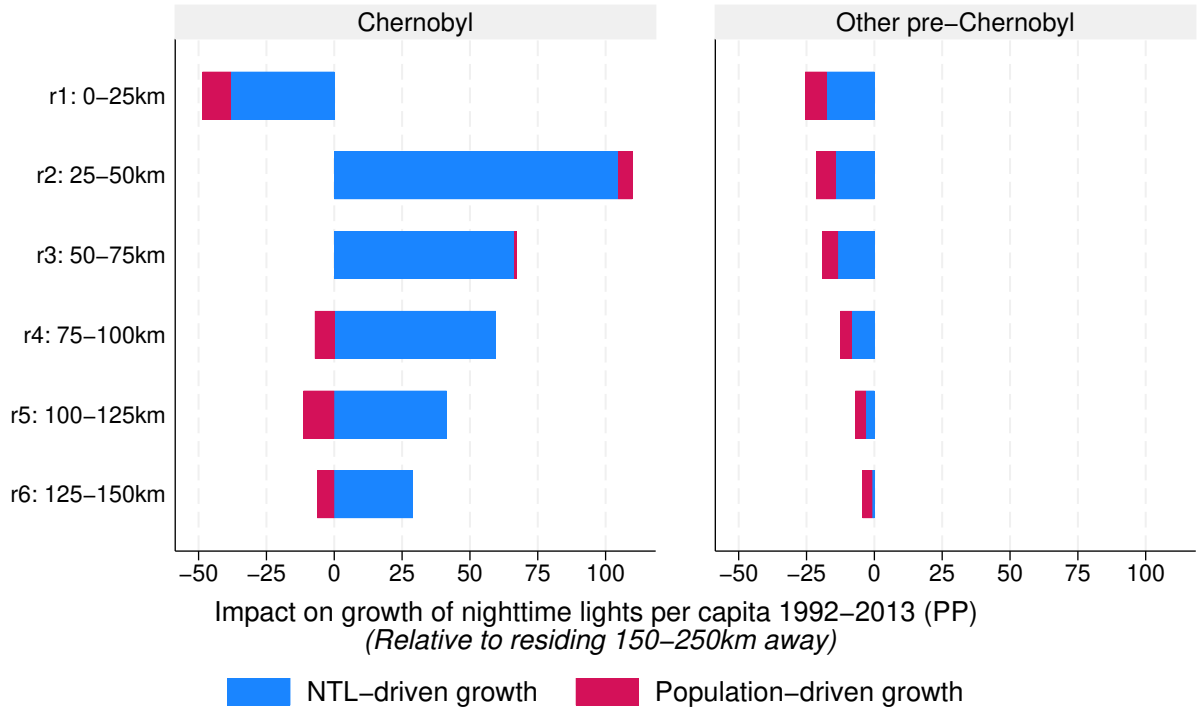
$$(\beta_0, \beta_{NTLpc}, ...) = (X'X)^{-1}X'\tilde{y}$$

$$(\beta_0, \beta_{NTL}, \beta_{POP}, ...) = (X'X)^{-1}X' \, ln(\frac{Y_{2013}}{Y_{1992}}) - (X'X)^{-1}X' \, ln(\frac{L_{2013}}{L_{1992}}) \tag{12}$$

Figure 5 depicts the estimation with separate contributions from nighttime lights growth and population growth. As noted earlier, the areas just outside the exclusion zone benefited in the form of labor productivity growth. These results show that most of the growth came from growth in nighttime lights. Interestingly, the Chernobyl nuclear disaster in rings two and three caused a slight increase in population-driven growth, meaning that it caused depopulation in these areas, which drove up nighttime lights per capita. Simultaneously, the disaster caused population growth in rings four, five, and six, which served as a per capita growth dampener.

The negative growth effects of non-Chernobyl NPPs was caused primarily by comparatively slower growth of nighttime lights in areas closer to the NPP, but also by population growth in these areas. The explanation of population growth in these areas is beyond the scope of this paper, but we surmise that it could be that these areas are sparsely populated and the NPP attracts workers to move to these areas to be close to their jobs. In any rate, the negative effect on nighttime lights means that increases economic activity in areas close to NPPs could not keep pace with the increased rate of population growth in these areas.

Figure 5: Source of impact of Chernobyl disaster: NTL-driven growth vs population-driven growth



Note: The figure is created using estimates from Equation 1, making use of the decomposition in Equation 12. Nighttime lights per capita utilizes DMSP-OLS data that are adjusted for issues of inter-calibration, blooming, and saturation. Population data come from the Global Human Settlement Layer. The Chernobyl sample contains only observations for which the closest NPP is Chernobyl. Control variables include population density in 1990, nighttime lights per capita in 1992, sum of nighttime lights in 1992, country fixed effects, land use fixed effects, reactor characteristics, elevation, ruggedness, maximum annual temperature, minimum annual temperature, and rainfall. Cells that had zero or missing nighttime lights per capita in 1992 or 2013 were excluded.

6 Conclusion

Understanding the impacts the Chernobyl disaster on economic development is critical element in understanding the economic history of countries most effected such as Ukraine and Belarus. On a wider scale, understanding the consequences of nuclear incidents is becoming increasingly important as a global shift to cleaner energy sources is underway. In this paper, we estimate the impact of the 1986 Chernobyl incident on labour productivity growth between 1992 and 2013. Exploiting the exogeneity of Chernobyl we estimate the direct effect of being located within 150km from both Chernobyl itself, as well as the perception effect of being located near other NPP's across the globe. To address endogeniety concerns between NPP location and growth we implement two instrumental variables, relative rainfall and relative elevation.

We find that cells closer to an NPP, compared to the baseline of 150-250km away, have weaker labor productivity growth. We also find a robust negative effect of the Chernobyl incident on growth in areas in proximity to NPPs which are not Chernobyl, indicating a perception effect. In contrast, areas surrounding Chernobyl (25-75km) in fact experience a positive growth effect in labor productivity. Through a decomposition exercise, we argue that this is due to the areas immediately outside the exclusion zone which saw significant growth in NTL data over the sample period. Our results are robust to several specifications and an extensive vector of controls. Our preferred specifications, with relative elevation as our instrument, we estimate that cells 1km further away from a non-chernboyl power plant experienced 0.69 percentage points stronger growth than the control group. In terms of a direct effect, we estimate a 1.9 percentage point weaker growth compared to the control, with a 1km increase in distance away from Chernobyl.

References

Banks, John and Kevin Massy (2012). *Nuclear Power in Developing Countries? Let's Talk about It*. URL: https://www.brookings.edu/articles/nuclear-power-in-developing-countries-lets-talk-about-it/.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman (Mar. 2003). "Instrumental Variables and GMM: Estimation and Testing". In: *The Stata Journal* 3.1, pp. 1–31. ISSN: 1536-867X. DOI: 10.1177/1536867X0300300101. URL: https://journals.sagepub.com/doi/abs/10.1177/1536867X0300300101.

Durand, Vanessa and Iossif Bogdevitch (n.d.). "Impact of the Chernobyl accident on agriculture-Countermeasures on agricultural areas". In: ().

Enercon Services (2024). *Michigan Nuclear Feasibility Study Report*. Tech. rep.

Goldemberg, José (2009). "Nuclear energy in developing countries ". In: *Journal of the American Academy of Arts and Sciences*. URL: https://www.amacad.org/publication/daedalus/nuclear-energy-developing-countries#.

Havenaar, Johan, Evelyn Bromet, and Semyon Gluzman (June 2016). "The 30-year mental health legacy of the Chernobyl disaster". In: *World Psychiatry* 15. DOI: 10.1002/wps.20335. URL: https://onlinelibrary.wiley.com/doi/10.1002/wps.20335.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil (2012). *Measuring economic growth from outer space*. DOI: 10.1257/aer.102.2.994.

Hijmans, Robert J. et al. (Dec. 2005). "Very high resolution interpolated climate surfaces for global land areas". In: *International Journal of Climatology* 25.15, pp. 1965–1978. ISSN: 1097-0088. DOI: 10.1002/JOC.1276. URL: https://onlinelibrary.wiley.com/doi/full/10.1002/joc.1276%20https://onlinelibrary.wiley.com/doi/abs/10.1002/joc.1276%20https://rmets.onlinelibrary.wiley.com/doi/10.1002/joc.1276.

Jha, Priyaranjan et al. (July 2024). "Impact of Colonial Institutions on Economic Growth and Development in India: Evidence from Night lights data". In: *Economic Development And Cultural Change* 72.4.

Karácsonyi, Dávid, Kazumasa Hanaoka, and Yelizaveta Skryzhevska (Sept. 2020). "Long-Term mass displacements-the main demographic consequence of nuclear disasters?" In: *The Demography of Disasters: Impacts for Population and Place*, pp. 15–48. DOI: 10.1007/978-3-030-49920-4{_}2/FIGURES/7. URL: https://link.springer.com/chapter/10.1007/978-3-030-49920-4_2.

Lehmann, H and J Wadsworth (2009). "The Impact of Chernobyl on Health and Labour Market Performance in the Ukraine". In.

Mehic, Adrian (2023). "The electoral consequences of environmental accidents: Evidence from Chernobyl". In: *Journal of Public Economics* 225.

Saha, Devashree et al. (2023). *To Shift Away from Oil and Gas, Developing Countries Need a 'Just Transition' to Protect Workers and Communities*. URL: https://www.wri.org/insights/just-transition-developing-countries-shift-oil-gas.

UNDP (2002). *The Human Consequences of the Chernobyl Nuclear Accident A Strategy for Recovery*. Tech. rep. International Atomic Energy Agency.

Zhao, Chenchen et al. (July 2022). "A consistent and corrected nighttime light dataset (CCNL 1992–2013) from DMSP-OLS data". In: *Scientific Data 2022 9:1* 9.1, pp. 1–12. ISSN: 2052-4463. DOI: 10.1038/s41597-022-01540-x. URL: https://www.nature.com/articles/s41597-022-01540-x.

A Appendix

Figure 6: Global NPP Construction by year

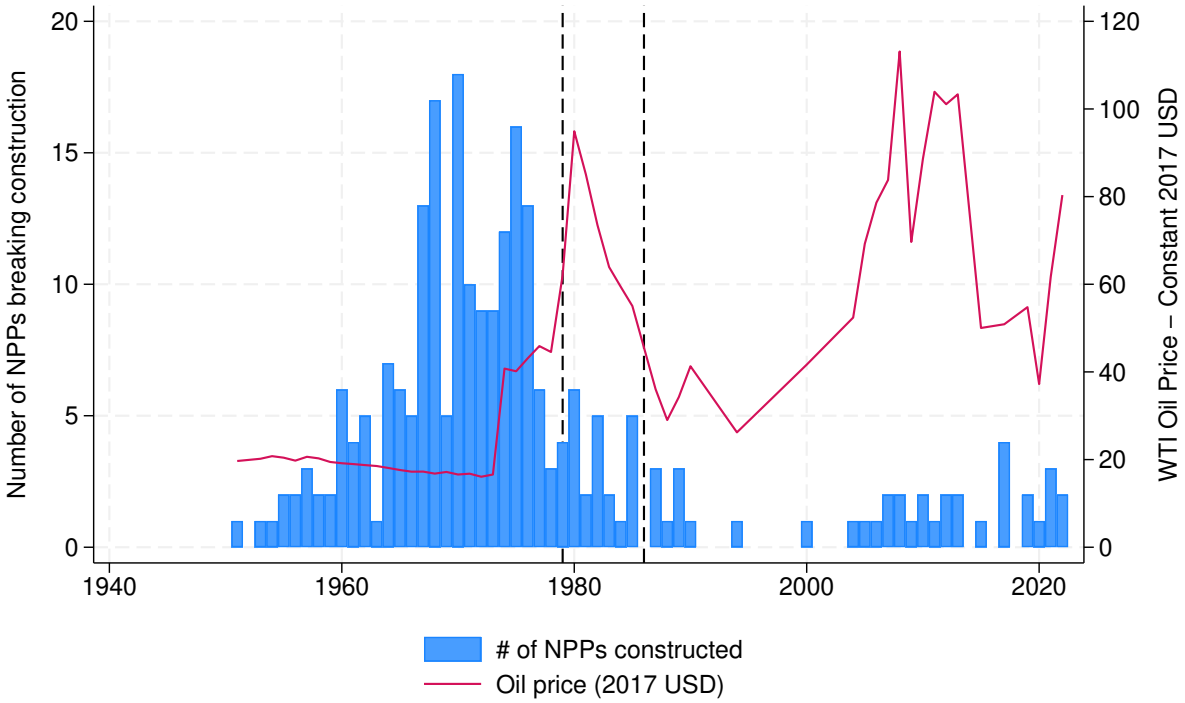


Figure 7: Ridgeline plot of labor productivity growth (NTL per capita) by ring, Chernobyl only

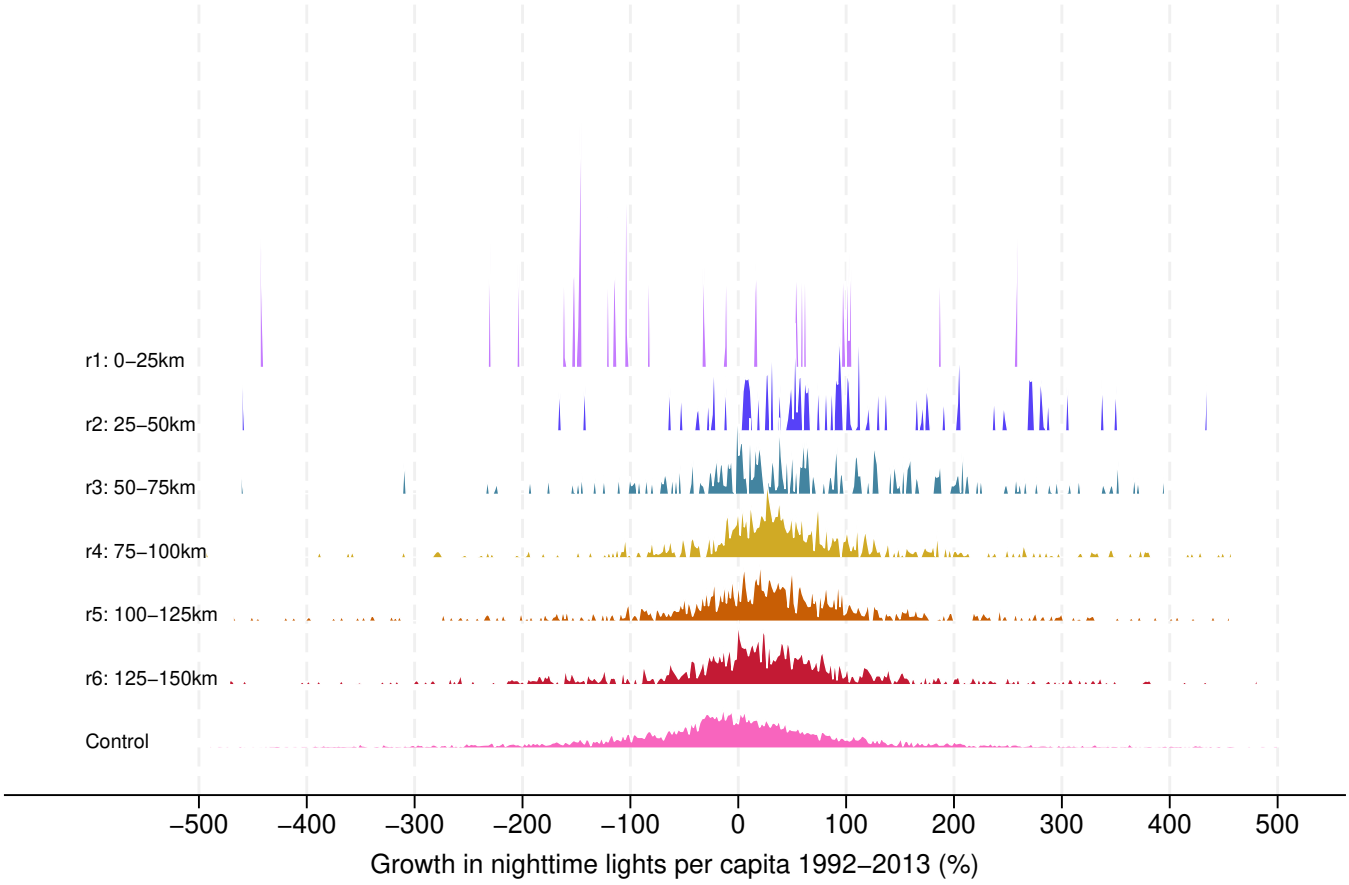


Figure 8: Visualisation of Nighttime Light Data

